A WALLEYE POLLOCK (*THERAGRA CHALCOGRAMMA*) DEPLETION ESTIMATOR FOR THE EASTERN BERING SEA

A

THESIS

Presented to the Faculty

of the University of Alaska Fairbanks

in Partial Fulfillment of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

BY

BRIAN CHARLES BATTAILE, B.S., M.S.

Fairbanks, Alaska

May 2005

A WALLEYE POLLOCK (*THERAGRA CHALCOGRAMMA*) DEPLETION ESTIMATOR FOR THE

EASTERN BERING SEA

By

BRIAN CHARLES BATTAILE

RECOMMENDED:

Milo Adkison

Mike Sigler

Brendan Kelly

Terrance Quinn II, Advisory Committee Chair

Director, Fisheries Division

APPROVED:

Dean, School of Fisheries and Ocean Sciences

Dean of the Graduate School

April 4, 2005
Date

Abstract

The decline of the Steller Sea lion in the eastern Bering Sea over the last 25 years has resulted in increased management of the pollock fishery due to requirements of the Endangered Species Act, as food competition was hypothesized to contribute to the decline. Our research focused on determining if the pollock fishery was causing significant depletion in the eastern Bering Sea, particularly in Steller sea lion critical habitat. DeLury depletion models were fitted to catch and effort data from 1995 to 1999, from the observer program, which required considerable processing to obtain a database at a temporal and spatial scale that is much finer than that used for stock assessment in the eastern Bering Sea. The catch per unit effort (CPUE) data were standardized in a unique way in that the data were stratified in space and time and standardized using separate general linear models for each stratum. A significant amount of depletion was detected in the pollock fishery from 1995-1999. Depletion estimates of fishery mortality tended to be an order of magnitude smaller than those found in traditional stock assessments. Post hoc analyses indicated that depletion is detected more easily in areas of low abundance due to the hyperstable relationship between CPUE and biomass, possibly exacerbated by a lack of search time in the model. Evidence further suggested that dispersing exploitation pressure decreases local depletion, and pollock may repopulate a depleted area within weeks. Finally, a hierarchical spatial Bayesian analysis with a conditional autoregressive model was constructed to unify the analysis. Because the data were relatively clean of outliers and not over dispersed, significant changes in

the results between the frequentist and Bayesian based analyses were not found as was little evidence of spatial autocorrelation in the estimates of catchability.

Table of Contents

LIST OF FIGURES

CHAPTER 1

CHAPTER 2

CHAPTER 3

CHAPTER 4

LIST OF TABLES

CHAPTER 1

CHAPTER 2

CHAPTER 3

Acknowledgments

This work would not have been possible without the help of numerous people. First and foremost is my advisor Terrance J. Quinn II with whom I share authorship with all the chapters in this text. His unwavering encouragement and patience in the light of my low mathematical self-esteem has resulted in an education I would not have previously thought possible. Milo D Adkison, with whom I share authorship on chapter 4, and is a committee member, has also been instrumental in this journey in which his normalcy has been especially inspiring. Special thanks also go to the other two committee members for their work on this project, Mike Sigler and Brendan Kelly. I share authorship of chapter 1 with Galen Tromble and David Ackley, and I would never have made heads or tails of the huge databases without David's help. I would also like to thank Andre Punt for significant help on chapter 2. The support of Susan Sugai has made my life much easier during this process. I would also like to thank the numerous students that have helped me along the way, including Erika Ammann, Kristin Cieciel, Dana Hanselman, Kalei Shotwell, Zac Hoyt, Ben Williams, Colin Schmitz, John Moran and Jamie Womble, who spent hours on the phone with me teaching me about a much maligned mapping program. Last but not least, Gabriella Hazelton and Louisa Hayes for all that they do so well. Finally, my parents Kenneth and Nancy Battaile and brother Kevin Battaile have provided me with support in all forms I could never begin to repay. This work was generously supported by the Alaska Sea Grant program.

General Introduction

This work was motivated by the decline of the Steller sea lion in the North Pacific Ocean over the past 30 years culminating in the 1997 listing of the western population as an endangered species and the eastern stock receiving a threatened designation under the Endangered Species Act. Among the many possible causes for the decline, food limitation has been a leading candidate. Pollock is a major food item for Steller sea lions and has been the source of a major fishery (over 1,000,000 metric tons/year) for many years; it has been hypothesized that local depletion of pollock by the industry may be a contributing factor to the decline of the sea lions. With the exact mechanisms of the decline still unknown, responsible management agencies are forced to limit human activities potentially associated with the Steller sea lion decline, ultimately resulting in fisheries working under increased regulation. However, the link from fishery exploitation to Steller sea lion decline has not been made. Unknowns include what percentage of the decline, if any, is due to food limitation, what percentage of the decline do to pollock and what impact the pollock fishery has on the ability for Steller sea lions to forage for pollock. While the very definition of fishing implies some degree of depletion of the resource, it is not known to what extent depletion occurs or if it is statistically detectable. It is the primary focus of this work to determine if the pollock fleet is causing statistically detectable depletion in the eastern Bering Sea and to quantify it in spatial and temporal terms.

The work is presented in 4 chapters. In chapter 1, the process of compiling the complete catch and effort records of the pollock fishery from 1995 to 1999 is described.

Three different data sources were merged in such a manner as to maximize the ability to determine if depletion is occurring. Chapter 2 describes the process of standardizing the catch and effort data, in order to eliminate the variability in the data related to vessel characteristics that would hide any depletion signal. In chapter 3 a depletion estimator is constructed and applied to the standardized catch and effort data. I also determined what, if any, spatial, temporal, environmental or fishery related characteristics were associated with depletion. In chapter 4, a hierarchical spatial Bayesian treatment is applied to the depletion estimator in order to spatially unify the analysis to better characterize the pollock fishery as a whole, and to investigate the methods of characterizing spatial autocorrelation in a Bayesian framework with fisheries data.

CHAPTER 1

A Catch Estimation Algorithm for the Walleye Pollock *Theragra chalcogramma* Fishery and Comparison to Similar National Marine Fisheries Service Databases[1]

Battaile, B., T.J. Quinn II, D. Ackley, and G. Tromble

ABSTRACT

As fisheries management entertains more complex objectives to ensure sustainable fisheries and ecosystems, reexamination of all aspects of data collection, data analysis, and management actions is needed. In particular, focus on fine spatial and temporal scales is becoming more common. A new spatially and temporally explicit database was constructed with this focus for the total walleye pollock (*Theragra chalcogramma*) catch in the waters off Alaska. Three sources provide information about pollock catches: the National Marine Fisheries Service observer program data; weekly processor reports to the National Marine Fisheries Service, and Alaska Department of Fish and Game fish tickets. The observer program database contains exact locations by longitude and latitude and dates. Fish tickets and weekly processor reports are much coarser in time (by cruise and week, respectively) and space (by Alaska Department of Fish and Game and federal reporting areas, respectively). Hence, obtaining spatiotemporal data at the finest scale requires maximum use of observer data. However, a significant portion of pollock catch is unobserved, so that it was necessary to combine the three data sources to provide a full accounting of catch. Comparisons were made to two National Marine Fisheries Service algorithms, the Catch By Vessel and Blend,

---

[1] Accepted by Alaska Fisheries Research Bulletin

presently used for fisheries management and analysis purposes. Estimated total catch was similar among the three systems, but the new database makes best use of the observer data and consequently is preferred for addressing fine-scale questions about pollock management.

1.1 INTRODUCTION

For fisheries management to be successful, removals from the affected fish populations must be accurately measured. Underestimation of removals from harvesting often leads to overestimation of stock abundance and underestimation of the effects of harvesting in assessment models (NRC 1998). These removals include retained harvest (landings), discards, and incidental mortality. Depending on the fishery, catch information may come from at-sea observers, dockside observers, dockside landing reports (tickets, slips), and/or catcher/processor reports (NRC 2000). In many fisheries, the collection of information can be viewed as a census: records are taken from all harvesters. All the same, it is rare for all types of information to be collected from all vessels (e.g., discards, specific location of catches), so estimation of some harvest-related parameters is necessary. Finally, many fisheries have a variety of sources of information that need to be blended together. How to perform this amalgamation of information from different sources has historically received little attention in the primary fisheries literature.

There are many reasons why database work has not found its way into the primary fisheries literature. The construction of a new database and the decisions about what to include are unique to the purpose of each database with respect to the raw input material and available resources. There are some obvious general guidelines to follow (Gayanilo et al. 1997), such as accounting of all catch and avoiding redundancy; however, generic recommendations governing all situations are likely impossible. The construction of databases even enters into the realm of professional database management instead of fisheries research. While all research and stock assessment begins with database construction, this task is often seen as a mundane and necessary evil on the road to more interesting publishable research. Literature on the subject tends to be in the form of government publications describing specific databases that may have a limited scope, such as a format for a trawl survey database (e.g., Hunter and Tremblay 1992). Other literature involves symposia or committee publications involved in assessing a specific region's or government entity's policy on data collection and management (e.g., Sulit and Inuoe 1994) in which specific recommendations can be made for specific problems.

The collection of fisheries related information for management purposes requires significant amounts of time, effort, and money and is often the most expensive component of fisheries management. As one example, the National Marine Fisheries Service (NMFS) North Pacific Groundfish Observer Program is an extensive effort to collect data from the commercial catch for fisheries management by the North Pacific Fishery Management Council (NPFMC) (MRAG Americas, Inc. 2000). The need for high quality fisheries data by North American fisheries management officials is underscored by symposia and governmental reports on fisheries sampling methodology (NRC 1998, 2000; Doubleday and Rivard 1983). While basic catch quantities are the prime statistic of such data collection efforts, use of ancillary data (e.g., spatial and temporal) that are collected can be effectively utilized in increasingly complex fishery analyses. As government agencies are consistently battling with budgetary issues, making efficient use of such data will assist in providing the taxpayer with the most bang-for-the-buck.

Little attention is given to the process between raw data collection and end user analysis. Here-in, we attempt to bridge that gap. Our objective is to compile a database accounting for all of the walleye pollock (*Theragra chalcogramma*) catches in the Bering Sea/Aleutian Islands and Western Gulf of Alaska (GOA) at the finest possible resolution of time, space, and catch weight. With such a database, it will be possible to explore fine-scale effects of human activities and other factors on the walleye pollock population.

We describe in detail the algorithm used to compile this database and compare the results (total estimated catch) to those of two current NMFS databases: the Blend system and the catch by vessel (CBV) system. These databases are used by NMFS for many of their management plans, stock assessments, and allocations. All three databases use the same raw data sources, and have the same basic objective of estimating total walleye pollock catch, but each has specific objectives, described below, that result in different treatment of the data sources.

1.2 MATERIALS and METHODS

1.2.1 Data sources

Three sources of data were used in database construction: the NMFS observer program data, Alaska Department of Fish & Game (ADF&G) fish tickets, and weekly production/processor reports (WPR) that processing vessels provide to NMFS.

The observer program began in 1973 to observe foreign groundfish vessels operating in U.S. waters. The Magnuson Fisheries Management and Conservation Act of 1976 simultaneously created the 200 nautical mile Exclusive Economic Zone (EEZ), began the Americanization of the fishery, and established the North Pacific Fishery Management Council. Americanization was nearly complete by the late 1980s but there was no observer coverage of the domestic fleet. Consequently, the Alaska Sea Grant College Program, NMFS, and NPFMC implemented the domestic observer program, starting in 1990, to gather data to manage the wholly domestic groundfish fisheries off Alaska.

The observer program currently deploys observers based on vessel length and type of fishery operations. The following regulations apply to catcher and catcher/processor (C/P) vessels using trawl gear: vessels 125 ft and larger in overall length are required to carry an observer 100% of the time; vessels that are between 60 and 125 ft in overall length are required to carry an observer for 30% of their fishing days in each calendar quarter in which they fish for more than three days. Catcher vessels deliver to either shoreside processors (land-based plants or stationary floating processors operating in state waters) or floating processors operating in the EEZ (C/Ps or motherships (vessels that operate solely as processors) in the offshore fleet); motherships are 100% covered by the observer program in the offshore fleet. Catcher vessels that deliver only unsorted catch from the trawl codends to processor vessels are not required to carry observers, because the hauls will be observed onboard the processor. Vessels under 60 ft do not have to carry an observer but they account for only a small percentage of the walleye pollock catch.

The haul weight recorded by observers comes from a weighing scale when the whole haul can be weighed. When direct weights are not obtained, a volumetric estimate is made, in which the volume of the catch is determined, such as the codend or bin volumes, and is then multiplied by the catch density from a sample of the catch or one prescribed by the target fishery (AFSC 1999). Since 1999, most of the walleye pollock catch has been directly weighed on flow scales. Observers on C/Ps and motherships observe every haul. On smaller boats observers are unable to directly estimate every haul, in which case, estimates of total haul weight by skippers are recorded. An algorithm is then employed by NMFS, which takes that vessel's nearest observed haul in space and time and applies the species composition to the unobserved haul.

The ADF&G fish tickets are collected by the state of Alaska and are required for any groundfish landed in state waters or delivered to plants and processing vessels operating in state waters. Required information includes the date fishing began, landing date, total cruise catch weights, fishing area, and vessel information. The WPR data is collected from all processors of groundfish, independent of federal or state jurisdiction, and includes information about area fished and final product weights totaled for the week, among other data.

Each data source records fishing location in a different way. The WPRs have the coarsest scale in using the federal reporting areas (Figure 1) covering large tracts of ocean. The fish tickets use ADF&G reporting areas, which are generally 30 x 34.5 nmi blocks (in the eastern Bering Sea), but are subdivided near shorelines to demarcate the 3 mile state waters line and local features. The observer program records haul retrieval and deployment location by latitude and longitude coordinates to the nearest minute. The coarser reporting areas can generally be found from information on the finer scales. Hence, with ADF&G reporting areas, one can find the federal reporting area and with the latitude/longitude coordinates, one can find the ADF&G reporting area.

1.2.2 The NMFS Blend system

The Blend system (Figure 2) is an algorithm used by NMFS to obtain estimates of total catch from shoreside and offshore WPRs, and observer reports. For the shoreside component, WPRs are the best source of total landed catch, however, when available observer reports are the best source for total catch including discards. Discards for unobserved vessels are estimated by multiplying known retained catch by estimates of discard rates from observed boats. Discard rates are determined by the ratio of the weight of the discarded species and the total retained groundfish weight classified by factors that define a fishery. Retained catch and estimated discards are combined for a total shoreside sector catch. For the offshore component, discards are accounted for by observers and estimated by the industry, so the Blend algorithm simply chooses between the WPR and the observer records for the corresponding week to account for the total catch. The WPR record is selected in favor of observer data according to these three rules: (1) if the total catch numbers from WPRs and observer data are within 5% of each other; (2) if the WPR is more than 30% greater in total walleye pollock than the observer total when walleye pollock is targeted; and (3) the WPR is more than 20% greater for all other groundfish species; otherwise, the observer record is used. Rules 2 and 3, which use the WPR data, are applied when it is thought that the observer data is grossly inaccurate.

1.2.3 Catch By Vessel database

With respect to walleye pollock, the Catch By Vessel (CBV) database was created to determine vessel eligibility and annual catch allocation requirements, based on historical individual vessel catch, as set forth by the American Fisheries Act passed into legislation in 1999. The two primary objectives of this database are to identify the harvesting vessel and to identify the ADF&G reporting area of catch. The ADF&G fish tickets, WPR reports, and observer data are combined to create a comprehensive database while minimizing any overlapping information. The CBV database uses a list of processors consisting of motherships and C/Ps operating in the EEZ for which fish tickets are not required. Landings delivered to these vessels (with 100% observer coverage) are represented by observer data. The ADF&G fish ticket database is the source for all other landings to processors not on this list. Fish ticket discard information is not included. The WPR data are selected for deliveries to all C/Ps on the list less than 125 ft in length.

1.2.4 Spatial and Temporal Scale Database

The primary data source for the spatial and temporal scale (STS) database is haul information from the NMFS observer program. For those boats or trips not covered by the observer program, ADF&G fish tickets from shoreside processors (for unobserved vessels delivering to shoreside processors) and WPRs from at sea processors fill in remaining data gaps. The observer database is our preferred source because it records catch weight by haul, haul time to the nearest minute from the ship's logbook, and location to the nearest minute in latitude and longitude. The ADF&G fish tickets record landings (generally weighed on scales), fishing location by ADF&G reporting area, the date fishing began, and occasionally estimates of discards, but does not record a more specific measure of effort such as haul time or number of hauls. The WPRs also lack effort data, report location using the coarse federal reporting areas only, and estimate weekly catch from finished product, making it the least desirable data source. Hence, any duplicate data from the three sources are always represented by the observer program in the STS.

1.2.5 Data algorithm for the STS

Figure 3 is a flow chart of expected percentages of data from the three source databases contributing to the STS. Theoretically catches from 70% of the fishing days of 60-125 ft vessels in the inshore sector are recorded only with ADF&G fish tickets. The approximately 30% of fish tickets also covered by the observer program were identified by vessel ID number and overlapping dates and matched by the following method. All observed hauls should have a corresponding fish ticket. Fish tickets record the fishing start date and the landing date while observer records show the date a haul takes place. Hauls for a specific vessel, recorded by the observer program, falling within or on fish ticket dates for the same vessel were removed by ordering the two sets of records by date on a computer spreadsheet. It was assumed that observers were present for a complete trip. Like the CBV, fish ticket discard information was not included.

Weekly processor reports for the offshore sector report a total catch estimate using an algorithm (performed by NMFS) to extrapolate weights of processed product to unprocessed catch weights. The WPR data were used for the offshore sector when there were gaps in the observer record. Data gaps could occur for unobserved 60-125 ft C/Ps (70% of the time) and in rare instances, for observer records determined by NMFS to be flawed.

The process of using WPR data was as follows. First, if all days within the WPR record were observed, or if observed catch exceeded WPR catch, then the WPR data were eliminated. Second, if observer coverage was incomplete for a week and when there was a positive difference between the haul estimates (WPR – observer), the difference was included in the STS. If WPRs indicate that fishing occurred in more than one federal area for the week, then the catch was partitioned over those areas. Finally, for weeks with no observer coverage, WPR haul weights were simply recorded for the STS.

1.2.6 Comparison between databases

Very little by means of formal statistical testing is applicable here as we are making a census of the catch and defining a selection process. We do however compare totals between the STS, CBV and Blend database from the observer, fish tickets and WPR sources. We further stratify the totals by ADF&G and federal reporting areas, vessel sizes, and processor categories to examine characteristics of the pollock fishery and how the information in the STS, CBV and Blend databases reflect the fishery.

1.3 RESULTS

Tables 1, 2, and 3 show the relative contributions of the three raw data sources, and the final total weights for the years 1995-1999 for the Blend, CBV and STS databases, respectively. The Blend system relies on observer records for approximately 50-70% of the BSAI data over these five years, with WPRs supplying the remainder (Table 1). In contrast, the WPRs are the dominant data source in the GOA (approximately 90%), because the smaller vessels of the GOA have less observer coverage.

The CBV system relies on observer data primarily with the remainder supplied from ADF&G fish tickets (Table 2). Clearly, WPRs contribute very little to the CBV. As in the Blend system, some differences occur between regions, with the GOA region heavily dependent on fish ticket data for the CBV.

The STS system relies on observer data for the majority of its source data in the BSAI (approximately 90%) and an insignificant amount on the WPR data (Table 3). The percentages of observer coverage for the STS are similar to that expected from Figure 3 for the medium-sized vessels of the inshore sector (Table 4) with ~70-80% from fish tickets and ~20-30% from observer records. As in the CBV, fish tickets supply the majority of the data for the STS in the GOA.

The total walleye pollock catch weight for each year from the STS database is consistently larger than that for the CBV by ~2.50% for 1995-98 and by 5.25% for 1999 (Table 3). The STS total catch is within -0.50% to 1.50% of that for the Blend system for 1995-98 and greater than that for the Blend by 4.25% in 1999.

Figure 4 graphically compares the relative contributions of catch from the source databases used by each database. The contributions for the BS and AI regions are relatively similar, but those from the GOA are quite different due to its heavier dependence on a shore-based fleet. The STS clearly contains the largest percentage of observer data, the CBV contains the largest percentage of fish ticket data, and the Blend contains the largest percentage of WPR data.

In order to examine the consistency among the databases, the proportions of catch by vessel size (small, medium, and large) for the STS, CBV, and Blend databases are graphically compared for each region and year (Figure 5). The CBV and STS databases on the middle and outer rings show nearly identical relative percentages of catch by vessel size indicating consistency through the source databases. The Blend database uses shore-based processor WPRs with no associated catcher-vessel length data; hence no comparison to the other databases can be made.

The percentages of observer data used in the CBV and STS databases change across ADF&G areas (Figure 6; the Blend database could not be included because its WPR data does not have location information at the ADF&G area level). In general, a lower percentage comes from observer records near shore and increases as the distance from the shore increases, and this trend is more pronounced in the CBV relative to the STS. Some northern areas show the CBV with a slightly greater percentage of observer data than the STS. This does not indicate that the CBV included observer data that the STS did not; instead, the STS algorithm included a small number (1-3) of fish tickets that the CBV did not. This could happen if a boat designated as "offshore" offloaded onshore. Similarly, a federal stratification shows the same general trend (Figure 7, including the Blend database) and also indicates the large differences between the percentage of observer data between the Blend and STS.

Unexpectedly large differences exist between WPR and observer, and fish ticket and observer records. For the 1995 data, we made a comparison of matched fish tickets and observer data and matched WPR and observer data (Table 5). The fish ticket/observer matched data are split into 2 groups, those within the walleye pollock season and those outside the walleye pollock season. During the walleye pollock season, the weights from fish tickets are relatively close overall (96%) to the observer data and individually, the geometric mean of the ratio of the individual fish tickets and their matched hauls is 0.95, quite similar to the expected ratio of 1. The off-season fish tickets are much different in total (444%) and individually with a geometric mean of the ratios of 27:1. The WPR data shows little difference in total weight when compared to the observer program but differences between individual records and their matched observer records are quite variable; coefficients of variation for WPRs with complete observer coverage and those with incomplete observer coverage are 780% and 96%, respectively.

1.4 DISCUSSION

The objective of the STS was to compile a database accounting for the total walleye pollock catch while maximizing spatial and temporal detail useful for the detailed fisheries analysis. As mentioned earlier, data from the observer program accomplishes this objective better than the other 2 data sources; hence, maximizing data from the observer source was the primary objective. Nearly 90% of the documented walleye pollock catch in the STS was taken from the observer program, 10% from the ADF&G fish tickets, while the WPR contribution represented less than 1% (Table 3, Figure 4). Nearly 100% of the database includes haul location to the level of ADF&G reporting area and nearly 90% includes effort data as haul duration to the minute and a spatial resolution for fishing location to the nearest minute of longitude and latitude. The CBV is made up of much more fish ticket data than the STS, and the Blend database has considerable percentages of WPR data, particularly in 1998 (Tables 1, 2, 3 and Figure 4).

Vessel size and sector differences affect the relative percentages of observer fish ticket and WPR data in a particular area. Very few vessels are under 125 ft in the offshore sector; hence most of these vessels were covered by the observer program. Thus, very little WPR data were incorporated in the CBV and STS databases. The GOA has relatively few larger boats, so less observer program data are utilized. The spatial differences in source data percentages between the CBV and STS shown in Figure 6 arise directly from the interaction between vessel size and observer coverage. These spatial differences show that no one data source alone can be used as a relative index of catch by area, because fish tickets cover a disproportionate number of near shore small vessels that are not observed.

In comparing the three methods, the STS system is quite close to the Blend and the CBV in total catch. The CBV has slightly lower percentages for total catch than the STS in the BSAI (Table 3). The 1999 STS totals are greater than the CBV and Blend by a few percentage points relative to the other years. In 1999, major changes in the walleye pollock fishery occurred due to the American Fisheries Act. It is also evident that the CBV has a larger percentage from fish ticket data in 1999 than in previous years, as did the STS. The STS is approximately 5% larger in both the GOA and BS areas. Catch in the AI is practically the same, but walleye pollock is only a bycatch component in this area in 1999. Also in 1999, the greatest percentage (81%) of catch (from fish tickets) of shore-based medium-sized vessels is about 10% larger than expected from Figure 3 due to new catch allocation from the American Fisheries Act.

The fundamental differences between the Blend, CBV, and STS stem primarily from main organizational categories under which the data are collected. The CBV is vessel oriented, hence the "catch by vessel" name. The Blend is processor oriented, hence WPR data are most prevalent. The STS is observer oriented and more similar to the CBV than to the WPR. With the CBV, vessel information was obtained such that one source of information, be it observer, fish ticket or WPR, could completely cover a category of vessels. Thus, the CBV avoided the matching of data that occurred in the STS and hence lessened the problems of date and time inconsistencies between observer, fish ticket, and WPR databases. Because the CBV and STS are most similar, comparison of the CBV database to the STS is perhaps most telling of the accuracy of the final haul weights found in the STS. In comparing the BSAI data, the greatest difference between the two databases is 5% (Table 5).

Differences between duplicate data reported in the observer data, WPR reports, and fish tickets, and the differences in how these are dealt with among the Blend, CBV and STS databases could explain the different yearly totals found among databases (Table 3). In compiling the STS, subsequent fishing trips would often have the same landing and start dates in the fish tickets, making it difficult to match observer hauls to a particular fish ticket on those dates. In addition, trip start dates have been found to be prone to error because they were recorded at the time of landing. Fish tickets and observer data covering the same hauls never report the same weights, although observer and fish ticket data for inseason large walleye pollock hauls (in the 10s to 100s of thousands of kilograms) were more similar than off-season hauls (Table 5). Fortunately, off-season catches are orders of magnitude smaller. Such problems could lead to differences between 2 databases that use different matching algorithms and different proportions of the fish ticket and observer data. The latter situation is especially problematic if either the fish tickets or observers tended to record larger amounts for the same haul. The inaccuracies of the fish ticket start and landing dates are probably the largest source of error for the STS. Fortunately, the inconsistencies between observer data and fish tickets occur in only about 10% of the fish tickets, which comprise about 10% of the STS, resulting in only 1% of the STS database with potential errors, a relatively small fraction. Hence, the errors are unlikely to cause major problems when using the STS for data analysis.

The large differences between off-season WPR and observer reports are somewhat disturbing. While off-season catch makes up a minute percentage of the total, its inaccuracies could have a significant impact on analysis investigating off-season catch. In such a case, further consideration should be given to determining which database is most accurate.

Discards from individual ADF&G fish tickets have not been included in the STS. They are recorded on the fish ticket as estimated by the fisher but not accurately measured during the fishing trip. For this reason, they have not been included here, a decision also reached in compiling the CBV dataset. One reason why the total catch from the STS is larger than that for the CBV may be because the CBV has a larger percentage of data from fish tickets and discards from these trips were excluded, whereas discards are included in the corresponding observer data. How discards are treated in the STS should be closely considered when using it for data analyses, as it may be significant. Average discard rates in the eastern Bering Sea from 1995-1997 and 1998-1999 averaged 7.3 and 2.25%, respectively (Ianelli et al. 2003).

1.4.1 Conclusion

The relative agreement of the three databases lends credence to the legitimacy of all three. While differing in their primary applications and hence, source data ratios, all three accurately depict the exploitation of the walleye pollock fishing fleet. The STS has significantly improved spatial and temporal resolution compared to the Blend and CBV databases, while still providing consistent annual total walleye pollock catch estimates The STS also uses the largest percentages of observer data, which are collected contemporaneously with the catching process. This study has shown that increased awareness of data management can maximize the utility (scientifically and financially) of available data.

1.4.2 Sponsorship

This publication is the result of research sponsored by Alaska Sea Grant with funds from the National Oceanic and Atmospheric Administration Office of Sea Grant, Department of Commerce, under grant no. NA 86RG0050 (project no. R/101-01) and from the University of Alaska with funds appropriated by the state.

LITERATURE CITED

AFSC (Alaska Fisheries Science Center). 1999. North pacific groundfish observer manual. North Pacific Groundfish Observer Program. Seattle, Washington.

Department of Commerce. 1997. Fisheries of the exclusive economic zone off Alaska; Improved retention/improved utilization. Federal Register: December 3, 1997. Volume 62 Number 232: 63880-63891.

Doubleday, W. G., and D. Rivard, (editors). 1983. Sampling commercial catches of marine fish and invertebrates. Canadian Special Publication of Fisheries and Aquatic Sciences 66.

Gayanilo, R. C., Jr., T. Stromme, and D. Pauly. 1997. Toward a generic trawl survey database management system. Pages 116-132 *in* G. Silvestre and D. Pauly, editors. Status and management of tropical coastal fisheries in Asia. ICLARM Conference Procedings 53.

Hunter, C. M. and M. J. Tremblay. 1992. A database for catch and length composition data related to the Scotia-Fundy lobster fishery. Canadian Manuscript Report of Fisheries and Aquatic Sciences 2149.

Ianelli, J. N., S. Barbeaux, G. Walters, N. Williamson. 2003. Bering Sea-Aleutian Islands walleye wollock assessment for 2003. In: Stock assessment and fishery evaluation report for the groundfish resources of the Bering Sea/ Aleutian Islands regions. North Pacific Fishery Management Council Anchorage, AK, Section 1:1-126.

MRAG (Marine Resources Assessment Group) Americas, Inc. 2000. Independent review of the north pacific groundfish observer program. Tampa Bay, Florida.

NRC (National Research Council). 1998. Improving Fish Stock Assessments. National Academy Press, Washington DC.

NRC (National Research Council). 2000. Improving the collection, management, and use of marine fisheries data. National Academy Press, Washington DC.

NMFS (National Marine Fisheries Service). 2000. Endangered Species Act-section 7 consultation, biological opinion and incidental take statement. November 30, 2000. National Marine Fisheries Service, Juneau, Alaska.

NOAA (National Oceanographic and Atmospheric Administration). 2002. 2003 Record keeping and reporting (R&R) – FIGURES, BSAI Statistical and Reporting Areas, 2002, National Marine Fisheries Service. http://www.fakr.noaa.gov/rr/figures.htm Accessed March 20, 2003.

Seber, G.A.F. 1982. The estimation of animal abundance and related parameters, Second edition, Griffin, London.

Sulit, V. R., and K. Inoue. 1994. Status of fishery information and statistics in Asia. Proceedings of the regional workshop on fishery information and statistics in Asia. Southeast Asian Fisheries Development Center (SEAFDEC) Secretariat, Bangkok, Thailand Vol. II: Report of the Workshop.

Table 1.1. Walleye pollock catch in weight (metric tons) by database source for the Bering Sea (BS), Aleutian Islands (AI) and the Gulf of Alaska (GOA) fisheries using the Blend system.

BS Source	1995	1996	1997	1998	1999
Observer records	785,275	732,745	648,864	515,454	549,014
WPR records	424,892	384,295	456,971	566,174	429,738
Estimated discards	15,076	13,803	18,758	2,247	10,444
BS Total	1,225,243	1,130,842	1,124,592	1,083,875	989,196
AI					
Observer records	71,082	75,598	12,948	18,290	1,087
WPR records	33,088	15,698	12,976	22,051	48
Estimated discards	90	201	16	1	385
AI Total	104,260	91,497	25,940	40,342	1,520
GOA					
Observer records	2,056	2,241	1,613	189	374
WPR records	64,857	47,048	85,211	123,965	93,438
Estimated discards	5,705	1,974	3,260	1,306	1,825
GOA Total	72,618	51,263	90,085	125,460	95,637
BSAI Total	1,329,503	1,222,339	1,150,532	1,124,217	990,717
BSAI-GOA Total	1,402,122	1,273,602	1,240,617	1,249,677	1,086,354

Table 1.2. Walleye pollock catch in weight (metric tons) by database source for the Bering Sea (BS), Aleutian Islands (AI), and Gulf of Alaska (GOA) fisheries using the catch by vessel (CBV) system. The total BSAI weight from the CBV system compared to the Blend system is shown as % BSAI of Blend.

BS Source	1995	1996	1997	1998	1999
Fish Tickets	410,412	389,228	352,756	364,900	433,545
Observer Reports	839,315	774,921	739,223	723,284	543,763
WPR records	34	203	69	1,022	1,237
BS Total	1,249,761	1,164,352	1,092,048	1,089,206	978,544
AI					
Fish Tickets	17,367	11,043	8,257	7,616	1
Observer Reports	45,518	18,151	18,742	15,937	737
WPR records				3	
AI Total	62,885	29,193	27,000	23,555	738
GOA					
Fish Tickets	66,637	49,244	87,102	131,941	94,957
Observer Reports	1,618	2,322	645	269	405
WPR records	0	45		43	79
GOA Total	68,256	51,611	87,747	132,253	95,442
BSAI Total	1,312,646	1,193,545	1,119,048	1,112,761	979,282
BSAI-GOA Total	1,380,902	1,245,156	1,206,795	1,245,014	1,074,724
%BSAI of Blend	98.88%	97.76%	97.45%	98.82%	98.92%

Table 1.3. Walleye pollock catch in weight (metric tons) by database source for the Bering Sea (BS), Aleutian Islands (AI), and Gulf of Alaska (GOA) fisheries using the spatial and temporal scale (STS) system. The total weight from the STS system compared to the catch by vessel (CBV) system is shown as % BSAI of CBV; the total weight from the STS system compared to the Blend system is shown as % BSAI of BLEND.

BS Source	1995	1996	1997	1998	1999
Fish Tickets	123,634	130,050	109,550	106,785	140,435
Observer records	1,157,131	1,061,254	1,005,102	1,012,020	888,747
WPR records	1,664	2,217	4,205	501	720
BS Total	1,282,430	1,193,521	1,118,857	1,119,306	1,029,902
AI					
Fish Tickets	2,164	949	882	490	
Observer records	63,386	27,643	26,524	22,226	739
WPR records	2				
AI Total	65,552	28,592	27,406	22,716	739
GOA					
Fish Tickets	37,343	33,686	58,623	85,661	67,849
Observer records	37,352	22,286	35,841	48,267	32,267
WPR records	792	946	513	66	97
GOA Total	75,486	56,918	94,976	133,994	100,213
BSAI	1,347,982	1,222,113	1,146,263	1,142,022	1,030,641
BSAI-GOA	1,423,468	1,279,032	1,241,239	1,276,016	1,130,854
% BSAI of CBV	102.69%	102.39%	102.43%	102.63%	105.24%
%BSAI of Blend	101.39%	99.98%	99.63%	101.58%	104.03%

Table 1.4. Total weight (in metric tons) of walleye pollock by medium-sized vessels (66-125 ft) accounted for by fish tickets in the spatial and temporal scale (STS), and the total catch by medium-sized vessels. The expected 70% coverage by fish tickets in 1995-1996, and increase to 81% coverage by 1999, are shown.

STS medium vessels	1995	1996	1997	1998	1999
Fish Tickets	150,044	150,632	150,097	168,434	193,513
Total	221,186	205,628	197,343	220,343	238,149
Fish Tickets/Total	68%	73%	76%	76%	81%

Table 1.5. Differences among observer data and weekly processor reports (WPRs) and fish tickets (FT) for 1995. Weights are in kilograms. Observer weights are always larger for the total comparison of each database. Complete coverage indicates WPR weeks that had observer coverage through the entire week, incomplete coverage indicates observers were present for part of the week. Inseason hauls indicate hauls made within the prescribed pollock season while off-season hauls were made outside of the pollock season.

	Fish ticket		WPR	
	Off-season Hauls	Inseason Hauls	Complete Coverage	Incomplete Coverage
Number of FT or WPR records	147	420	70	119
Total FT or WPR weight	604,000	74,749,000	1,738,000	2,055,000
Corresponding observer weight	2,684,000	77,133,000	1,766,000	2,091,000
Total difference	2,080,000	3,384,000	28,000	36,000
Percent difference of observer to FT or WPR	444%	4.4%	1.6%	1.7%
Observer haul average	18,259	143,370	31,530	21,117
Mean difference between individual observer and WPR or FT records	14,146	8,057	614	2,529
CV of mean difference	7.2%	23%	780%	96%
Ratio (observer:WPR or FT) geometric mean	27.07:1	1.05:1	1.10:1	1.33:1
CV of geometric mean	38%	38%	90%	1105%

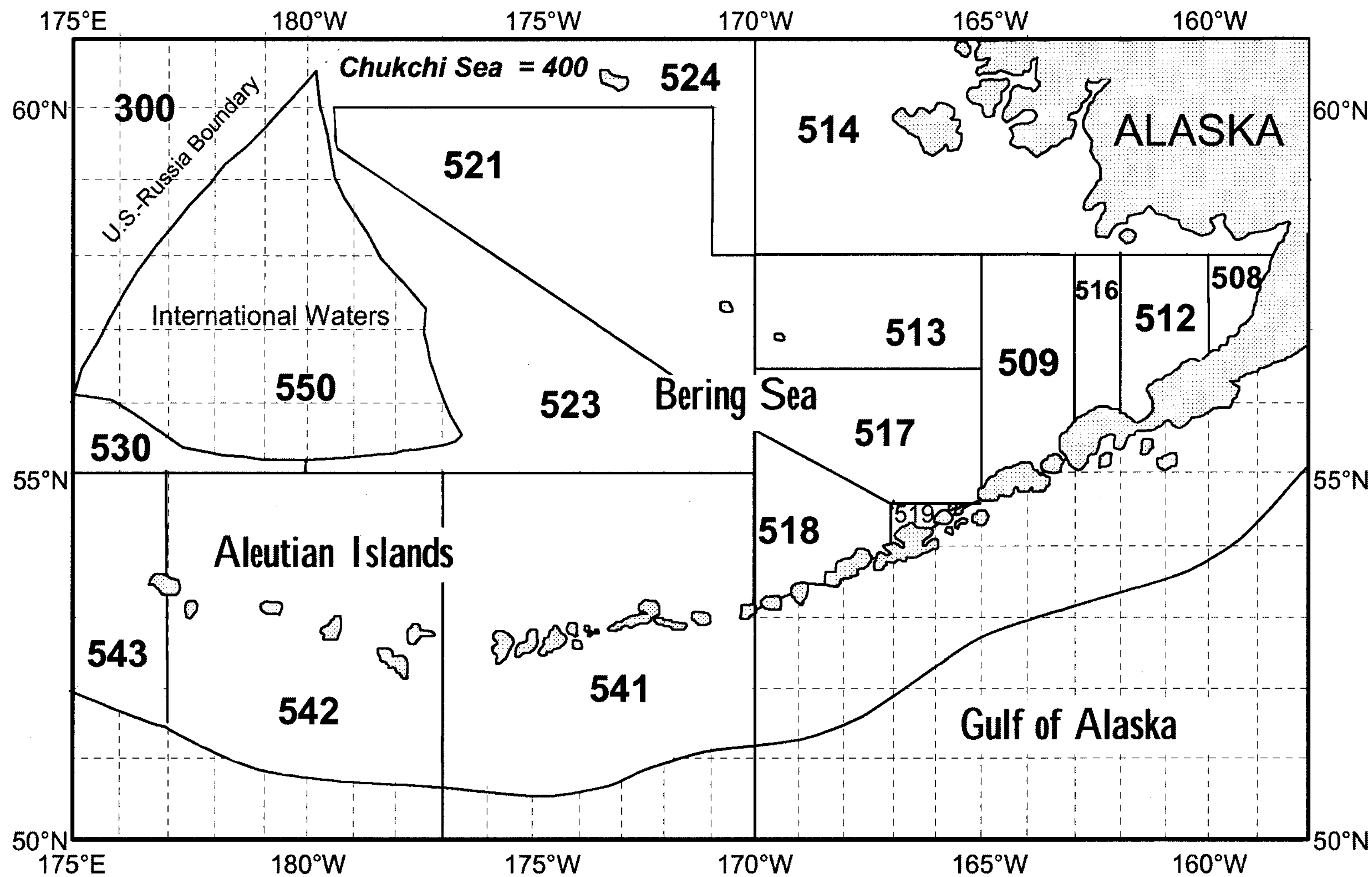


Figure 1.1. Map of the Bering Sea/Aleutian Islands and Gulf of Alaska detailing the federal reporting areas (NOAA 2002).

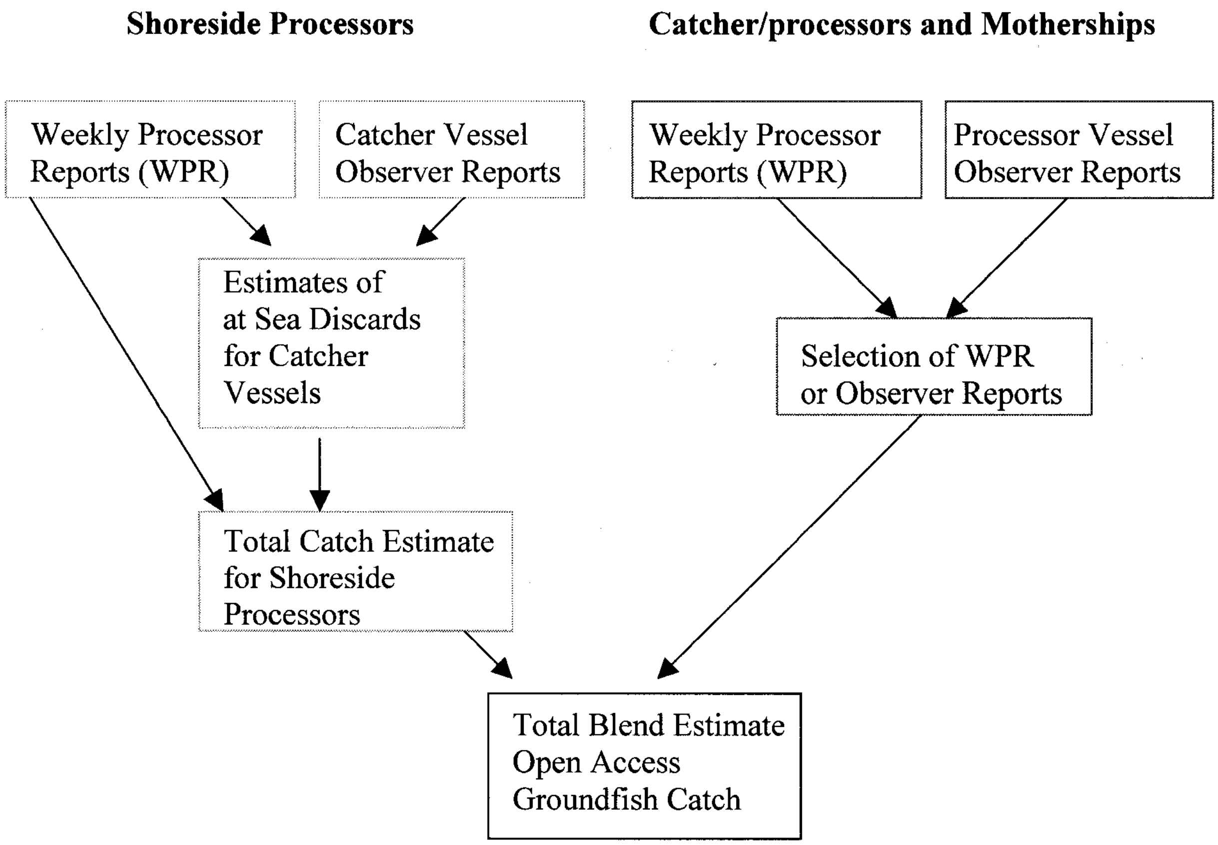


Figure 1.2. Flow diagram of the Blend system used by NMFS to monitor walleye pollock catch.

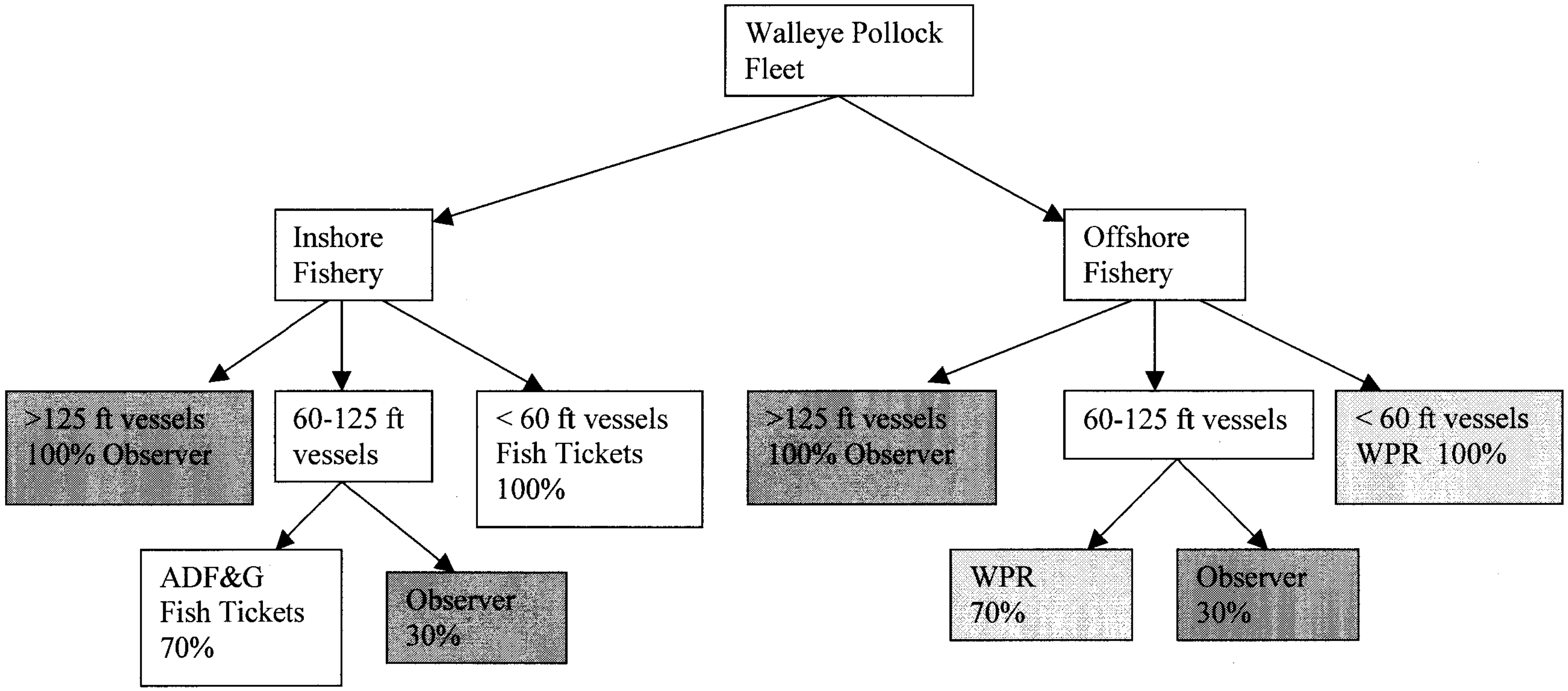


Figure 1.3. Flow diagram for data sources used in the catch estimation algorithm: data sources include observer coverage (Observer), Alaska Department of Fish and Game (ADF&G) fish tickets and weekly processor reports (WPR). Approximate percentages of fishing trips covered by each data source in each sector (Inshore, Offshore) are given.

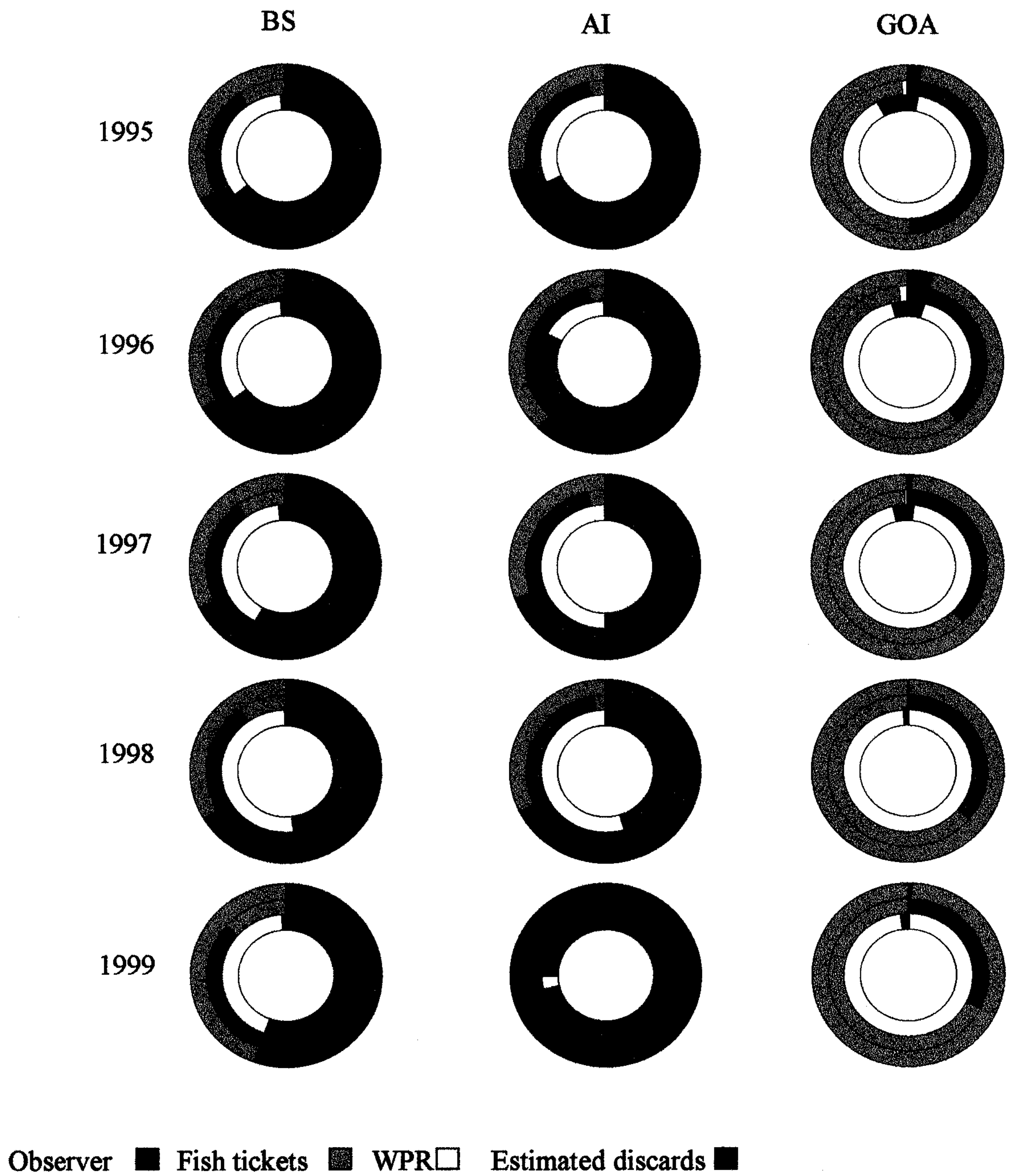


Figure 1.4. Estimated relative proportion of walleye pollock catch and discards by source database categories using the Blend (inner ring), spatial and temporal scale (STS) (middle ring) and catch by vessel (CBV, outer ring) databases.

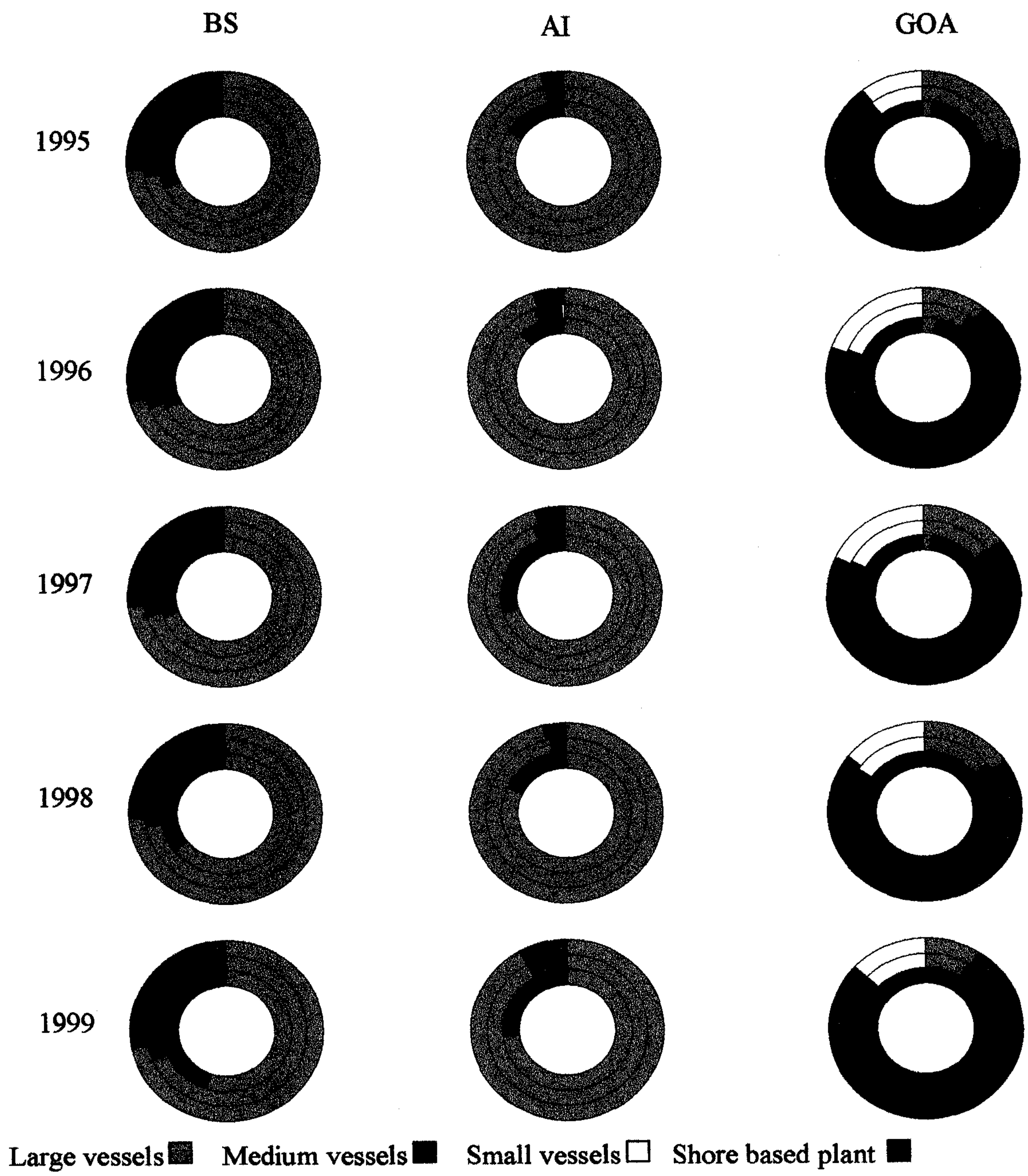


Figure 1.5. Estimated relative proportion of walleye pollock catch and discards by vessel size or processor categories using the Blend (inner ring), spatial and temporal (STS) (middle ring), and catch by vessel (CBV, outer ring) databases.

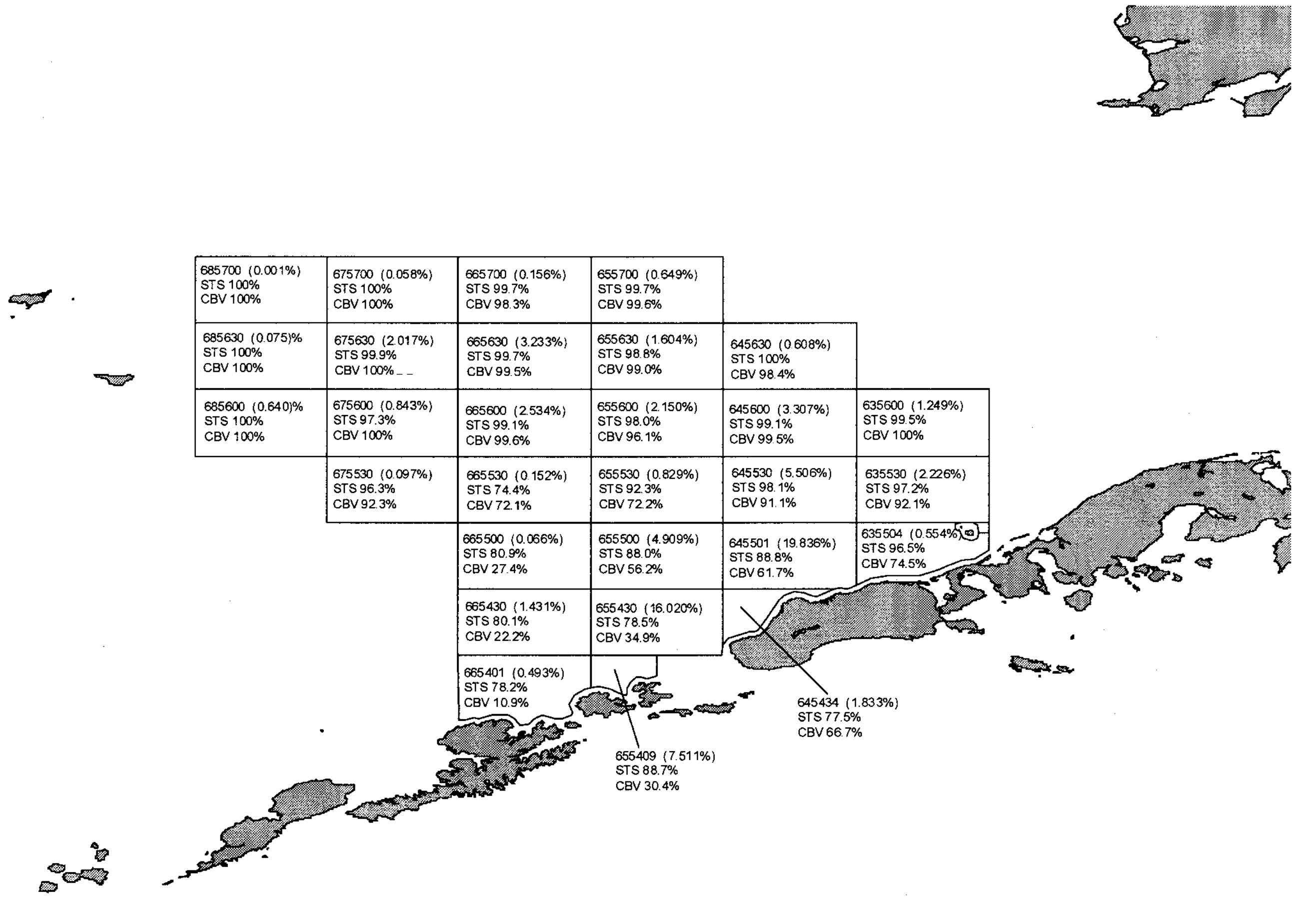


Figure 1.6. Relative percentages of observer program data for the catch by vessel (CBV), and relative and spatial and temporal scale databases (STS) aggregated by Alaska Department of Fish and Game (ADF&G) reporting areas. The 6-digit number is the ADF&G reporting area code, followed by the percentage of the total database by weight assigned to that area. The STS and CBV percentages indicate the percentage of data in that area that comes from observer program data.

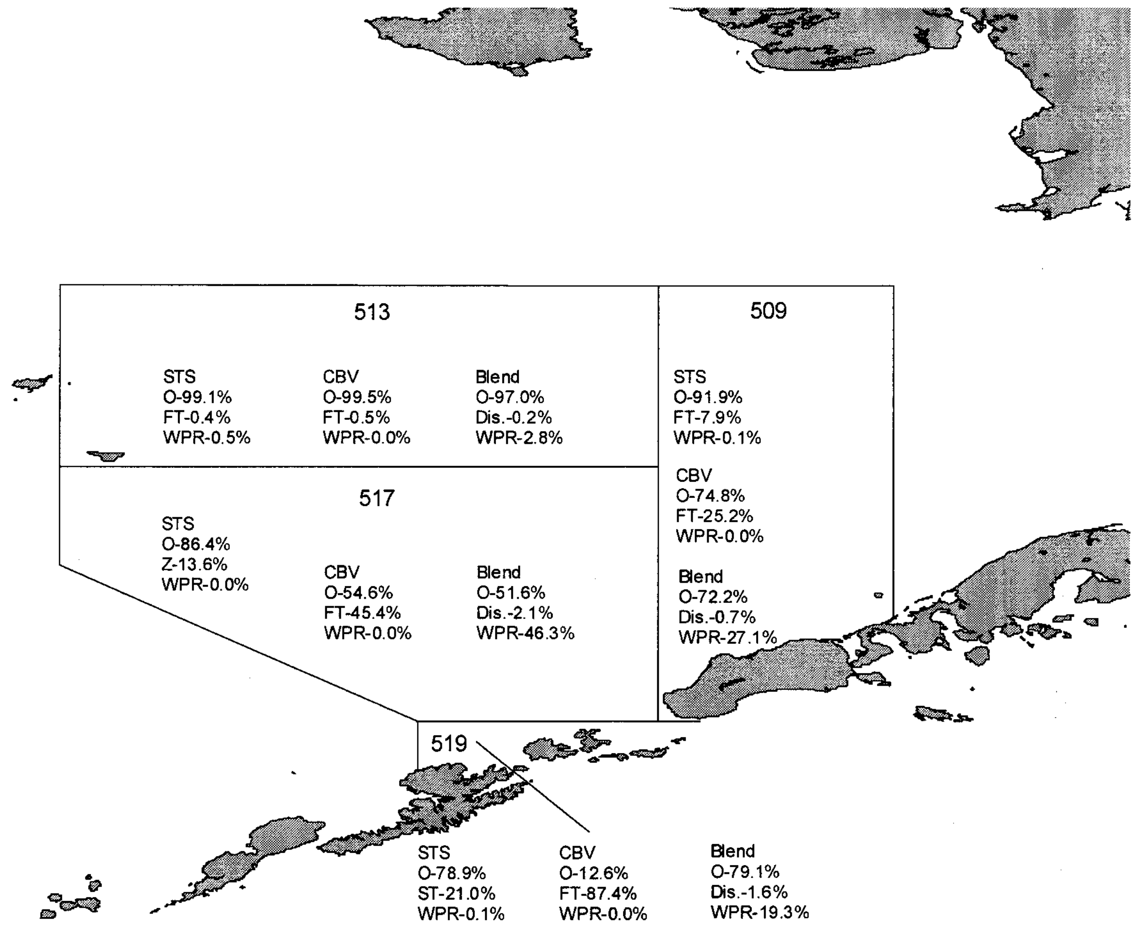


Figure 1.7. Relative percentages of observer program data for the catch by vessel (CBV) and spatial and temporal scale (STS) and Blend databases aggregated by Federal reporting areas reporting areas. The 3-digit number is the Federal reporting area code. The percentages indicate the percentage of data in that area that comes from observer (O) program data, fish tickets (FT), discards (Dis) and weekly processor reports (WPR).

CHAPTER 2

Catch per unit effort standardization of the eastern Bering Sea walleye pollock (*Theragra chalcogramma*) fleet[2]

B.C. Battaile, T.J. Quinn II

ABSTRACT

A general linear model (GLM) was used to standardize catch per unit effort (CPUE) data for Alaska walleye pollock (*Theragra chalcogramma*) from the Bering Sea and Gulf fleet for the years 1995-1999. Data were stratified temporally by year and season and spatially by area using either Alaska Department of Fish and Game (ADF&G) or National Marine Fisheries Service (NMFS) reporting areas. Four factors were used: vessel identification number, vessel speed, percentage of pollock by weight in the haul (a measure of targeting), and whether most of the haul took place before or after sunset. At least twenty-nine combinations of main effects, quadratic covariates, and interactions were tested for each year / area / season strata. GLM models explained from 31-48% of the total sums of squares. Vessel identification number was included in all models and explained the most variability. Of the remaining factors, the square of the percentage of pollock in the haul was included in most models, following an F test to determine parsimony. Analysis of the vessel identification number coefficients indicated that larger vessels tended to have higher CPUEs; and that this relationship differed between dedicated catcher vessels and offshore catcher processors. Coefficient estimates and response surfaces generally indicated increased CPUEs with the percentage of pollock in

[2] Published as Battaile, Brian C. and Terrance J. Quinn II. 2004. Catch per unit effort standardization of the eastern Bering Sea walleye pollock (*Theragra chalcogramma*) fleet. Fisheries Research 70:161-177

the haul and showed mixed results with vessel speed. The vessel identification number incorporated most vessel characteristics, leaving vessel speed primarily as a fitting variable with less biological meaning. The year / area / season stratification procedure was found to be necessary due to the unbalanced design, which otherwise would have factor levels with no data in a large combined model. In addition, the stratification procedure reduced the variability in CPUE substantially.

Keywords: Walleye pollock; Catch-per-unit-effort (CPUE); Standardization; General linear model (GLM)

2.1. Introduction

Hilborn and Walters (1992) suggested that the management of fisheries will improve more from a higher quality of collected data and less with advances in stock modeling. Numerous previously large fisheries for species such as Atlantic cod (*Gadus morhua*) (Rose and Kulka, 1999), Peruvian anchovy (*Engraulis ringens*), and North Sea herring (*Clupea harengus*) (Hilborn and Walters, 1992) have been reduced to economic extinction or fractions of their unfished biomass in part due to management actions based on ambiguous data. Walleye pollock (*Theragra chalcogramma*) rivals these historically important populations in size and importance. The eastern Bering Sea stock supports one of the largest fisheries in the world, with an estimated age 3+ biomass of over 11 million tons and 1.39 million tons harvested in 2001 (Ianelli et al., 2002). Accurate data are and will continue to be essential to the future productivity of the pollock fishery.

The data collected from those prosecuting a fishery likely have greater coverage in space and time (Vignaux, 1996) and are economically cheaper to collect than data collected by fishery-independent surveys (NRC, 2000). Catch and effort information is relatively easy to collect, and catch per unit of effort (CPUE) is sometimes used as an index of abundance in modern stock assessments (Quinn and Deriso, 1999). CPUE information can improve abundance estimates of commercial species (Fox and Starr, 1996). In the case of the eastern Bering Sea pollock, trained on-board observers collect CPUE data. The observer coverage amounts to 1-1.3 million metric tons of catch, from 36,000-50,000 observed pollock hauls for each of the years 1995-1999, which is a sizeable database of significant importance to pollock managers.

CPUE data should be used cautiously, however, because CPUE may not be an accurate index of abundance (NRC, 2000). In extreme cases, its improper use can contribute to the demise of fisheries when assumptions are not met adequately (Rose and Kulka, 1999). Also, the relationship between CPUE and abundance may not be linear (Bannerot and Austin, 1983; Richards and Schnute, 1986; Harley et al., 2001). In addition, in a fishery of mixed vessel and gear types, variations in fishing power among vessels will create variations in CPUE unrelated to abundance. Pollock vessels in the Bering Sea and Gulf of Alaska vary widely in size and functionality, from shore-based vessels under 60 feet in length making trips lasting only days, to large catcher processors hundreds of feet in length operating around the clock for weeks. Clearly, spatial and temporal processes can affect CPUE via habitat differences over space and environmental fluctuations over time, altering stock characteristics in qualitative and quantitative ways.

It is therefore vital to standardize CPUE for differences among and within vessels as well as for spatiotemporal differences. Finally, standardization highlights factors causing variability in catchability, leading to a better understanding of fishery dynamics (Goñi et al., 1999).

Baranov may have been the first to use CPUE in fisheries (Dunn et al., 2000). Allen and Punsley (1984) and Westrheim and Foucher (1985) provided a brief history of the use and methods of standardization of CPUE in fisheries, which started in the mid 1950's. Mathematically, standardization is a simple process involving the comparison of CPUE data from multiple sources by accounting for various factor effects through the use of a general linear model (GLM) (Hilborn and Walters, 1992, p.209–210; Quinn and Deriso, 1999, p.18–23).

The primary objective of this paper is to standardize the CPUE data of the eastern Bering Sea midwater pollock fishery. Typically, standardization is performed so that CPUE is comparable across the entire spectrum of a fishery for ultimate use as an index of abundance in stock assessment. However our goal is not to provide an index of abundance across space and time. Rather it is to eliminate other effects (related to vessels) prior to studying spatial and temporal effects. We stratified the data in space and time prior to standardization, because our interest is in relating the trend in CPUE over time within a season to local depletion. The stratification provides independent replicates for use in a temporally and spatially explicit DeLury abundance/depletion model (DeLury, 1947). Thus, the purpose of standardization was to eliminate vessel-related effects, so that the remaining variability can be related to biological factors in later studies. Fig. 1 shows one example of an obvious relationship of increasing CPUE with vessel size to illustrate the need for standardization.

2.2. Methods

2.2.1 Database preparation

We assembled a data set for the years 1995-1999. Catch and effort data used here were collected by onboard observers under the direction of the National Marine Fisheries Service (NMFS). Effort is measured as haul time in minutes. Total catch is extrapolated from samples to the total weight of the haul. If a haul is not sampled by an observer, its catch species composition is determined from a "nearest neighbor" sampled haul, captain estimates of total haul weight, and time using an algorithm developed by NMFS. Details of the accounting of pollock catch for the eastern Bering Sea fishery has been documented in a manuscript by Battaile et al. (unpublished).

NMFS divides the pollock fishery into seasons, and areas via inshore and offshore sectors. From 1995-1998, the seasons were roughly split between a winter A season from January to March and a fall B season from August to October. In 1999 the seasons were split further due to the passage of the American Fisheries Act and Steller Sea Lion endangered species management measures, into two winter seasons (A1 and A2) covering January through April, a B season covering August and September, and a C season covering September through November. Seasons are further subdivided into inshore and offshore sectors for reporting purposes by NMFS. However, the seasons for the inshore and offshore sectors took place at roughly the same time so we pooled data from the inshore/offshore sectors with the season length being the longer of the two.

In order to determine whether the results of the standardization depend on the spatial scale of the data, we examined two existing spatial stratification approaches that utilized the same data: Alaska Department of Fish and Game (ADF&G) and United States federal reporting areas (Fig. 2). The larger U.S. federal reporting areas are zones used by the NMFS. The smaller ADF&G reporting areas are used by the state of Alaska for management and generally consist of 30 by 30 nautical mile blocks.

Data were eliminated from the analysis for several reasons. Only observer program data were used because the other two potential data sources for pollock catch (ADF&G fish tickets and weekly processor reports) do not include haul duration, which is the measure of effort. Data were also eliminated from the standardization because: (1) pollock catch occurred in the off-season in other fisheries, (2) pollock was not the target of the haul and (3) haul duration, vessel speed, total catch, vessel identification (ID) number, season or area was not recorded.

The percentage of pollock relative to all other species combined in the haul is an index of pollock targeting; a small percentage could indicate tows capturing pollock that were not targeted, or tows targeting pollock with a large incidental bycatch. Large incidental bycatch is rare though, because the pelagic pollock fishery is quite clean. We excluded hauls with less than 50% pollock to use only data from vessels targeting pollock based on advice of pollock managers.

For the federal reporting areas, only those area / season strata with 100 or more observations were used. For the ADF&G areas, CPUE data from the 20 area / season combinations with the greatest total haul weights were standardized, because vessel effects are most likely to be estimable for areas with the greatest effort and catch. While some hauls might be misidentified as belonging in the pollock season when they were in fact conducted in other fisheries due to the combination of the inshore and offshore seasons, this was unlikely to adversely affect the standardization because off-season hauls are unlikely to be above 50% pollock and therefore, not included in the analysis.

2.2.2 CPUE standardization model

First, pollock CPUE data on a haul-by-haul basis were normalized by the natural logarithm transformation, which is a standard transformation for CPUE data (e.g., Megrey, 1986). The ln CPUE variable was standardized for individual vessel, vessel speed at the time of haul, and the percentage of pollock in the haul. Quadratic and interaction variables for the latter two continuous variables were included to permit response surface analysis (see below). For 1998-1999 the start and end times of fishing, in addition to total haul times, were recorded, allowing an additional factor based on the time of day of the haul to be considered. The factor "Day" was calculated by finding the sunrise and sunset time for the latitude, longitude, and date of the haul using the algorithm of Pelletier (2003). The haul was classified as a night or day haul depending on whether the timing of the middle of the haul occurred between sunset and sunrise or between sunrise and sunset, respectively. Vessel speed was measured in knots.

Vessel ID is a unique vessel number assigned by ADF&G. Exploratory data analysis revealed that among-vessel differences were large no matter what combination of factors was used; hence, we used the unique vessel ID number as a factor in all models.

Our standardization methodology is influenced by the assumptions of the DeLury estimator including a closed population and constant catchability, because our ultimate goal is to use the standardized data with this estimator. We minimize violating these assumptions by stratifying by space and time. While most standardizations include space and time factors in a single model (e.g., Quinn, 1987; Punsly and Deriso, 1991; Large, 1992), our stratification scheme involves performing separate standardizations for each time / space stratum as opposed to treating space and time as separate model factors in the analysis. The data set is unbalanced. The stratification therefore makes is possible to carry out the GLM procedure: if the data were not separated by area and season, there would be many combinations of factor levels for which there would have been no data. This problem results because a large number of vessels fish in only a few areas. For example, over half the vessels in 1995 fished in 9 or fewer ADF&G areas (Fig. 3). The CPUE data were stratified by year, season and once for the federal reporting area scheme and once for the ADF&G reporting area scheme, e.g., 1995, season A and federal reporting area 509.

The standardization was accomplished using a fixed effects analysis of variance (ANOVA) model fitted using S-Plus (MathSoft, 1999). Type III sums of squares (Milliken and Johnson, 1984) were utilized due to an "unbalanced design" where factor combinations had unequal numbers of observations. The model contains the four factors described previously: "Vessel ID" - the ADF&G vessel ID number, "%Pollock" - the percentage of the total catch in weight that consists of pollock, "Speed" - the speed of the vessel during the haul, and "Day" - whether the haul took place at night or during the day. Vessel ID and Day are categorical variables while the other two variables are continuous. To improve explanatory capability, the interaction variable Speed*%Pollock and the two quadratic variables Speed^2 and $\%\text{Pollock}^2$ were also included. Because the vessel ID factor has so many levels (one for each vessel), interactions between this factor and other variables could not be estimated. A subset of all possible combinations of factors was analyzed in order to make the analysis feasible. The full model (with inclusion of the Day factor for 1998 and 1999) is

$$\ln \text{CPUEfit} = \beta_0 + \beta_1 * \text{Vessel ID} + \beta_2 * \%\text{Pollock} + \beta_3 * \text{Speed} + \beta_4 * \%\text{Pollock}^2 + \beta_5 * \text{Speed}^2 + \beta_6 * \text{Speed} * \%\text{Pollock} + \beta_7 * \text{Day}.$$

Given that each model always included the vessel ID factor, the models for 1995-1997 included: the full model with 6 terms, three models with 5 terms in which a quadratic term or interaction was eliminated, nine 4-term models of all possible combinations given at least one main effect was included, ten 3-term models of all possible combinations, five 2-term models with one of the five factors, and one model with just vessel ID. As a result 29 models (58 for 1998 and 1999 for which the Day factor is available) were available for each year / season / area stratum, resulting in a total of approximately 8 350 models.

The most parsimonious model was found using a likelihood ratio F test (Quinn and Deriso, 1999, p.152):

$$F = \frac{\dfrac{(RSS_2 - RSS_1)}{(df_2 - df_1)}}{RMS_1}$$

where *RSS* is the residual sum of squares, *df* is the degrees of freedom, and *RMS* is the residual mean square. The subscript "1" refers to the full model and the subscript "2" to the reduced model.

Our use of 50 %Pollock for the cut-off point for inclusion into the analysis is examined. We demonstrate differences in CPUE based on the percentage of pollock in the haul and examine the sensitivity of the models to this 50% cut-off.

An additional problem that emerges when using %Pollock as an independent variable is that pollock catch is involved in both this variable and the dependent variable (ln CPUE), so we also examine the correlation between the catch of pollock and %Pollock.

2.2.3. Explanatory variables

The model results are ideally suited for response surface analysis (Schnute and Mckinnell, 1984) of the continuous variables Speed and %Pollock. Response surfaces describe the effect of the various factors on the dependent variable (ln CPUE) graphically. The main, quadratic, and interaction terms all combine to affect the behavior of the response variable, so that inspection of the individual model coefficients is usually uninformative. Instead, the response of the dependent variable as a function of two factors can be displayed on a three-dimensional graph providing an easily interpretable visual aid for understanding the factor effects.

2.2.4 Post-hoc analysis and stratification

We quantified the explained variability due to stratifying by area and season. GLM models were run on pooled data across seasons and areas for each year and area stratification type (five years and two area stratification types for a total of 10 analyses). The total sum of squares for the pooled data was then compared with the combined total sums of squares over strata. The difference between the two is the variability explained by the area and season stratification.

Finally, we determined whether the vessel ID coefficients could be explained by data on general vessel characteristics. A stepwise regression function procedure using S-Plus was performed on the vessel ID coefficients from the original standardizations using vessel length, gross tonnage, shaft horsepower and vessel type (catcher vessel, catcher/processor) and their squares as predictors. Other vessel-specific gear characteristics were not available. Data were pooled across the year, season, and area strata and the ADF&G and federal stratifications were investigated separately.

2.3. Results

2.3.1 General model

After removing incomplete or inappropriate data, 67-75% of the total pollock catch remained available for standardization (Table 1). Table 1 also shows that this catch was landed by a relatively small percentage of the total number of hauls that caught pollock (20-28% of the total). By using federal areas with 100 or more observations, nearly

100% of the data remaining upon cleaning were available for standardization. For the ADF&G stratification, the top 20 areas for 1995 include 77% of the cleaned catch (by weight), while the next 30 areas contribute only another 15%. Similar results were obtained for 1996-1998. Slightly lower percentages occurred for 1999 (55% for the top 20 ADF&G areas) due to decreased concentration of the catch in space and time.

The model sum of squares averaged over areas for a particular year and season ranged from 36 to 48% of the total sum of squares (Table 2). Vessel ID accounted for most of the explained variability (25-40%), greater than the variability explained by any other factor in Table 2 by an order of magnitude. Averaged over years and seasons, the model accounted for 42.4% of the variability in ln CPUE, of which 29.7% was due to vessel ID. The factor proportions in Table 2 do not add up to the percentage explained, because the explained sum of squares for each factor is calculated using the Type III method in which each contribution is calculated as though it were the last factor added on to the typical Type I sum of squares calculation. It is most appropriately viewed as an index of the relative proportion of explained variability attributable to each factor.

Fig. 4 shows the relationship between the percentage of pollock in a haul and ln CPUE, indicating that most of the hauls have either a low (<40%) or very high (>80%) %Pollock with few hauls between 40% and 80%. Table 3 displays the results of a standardization using data for ADF&G area 645501 season A 1995 based on four different %Pollock cut-off points: 0% (which uses all hauls), 50% and above, 75% and above and 90% and above. Table 3 indicates that coefficient values can differ markedly depending on the choice of the cut-off, with the values for 75% and 90% being fairly similar. However, Table 4 indicates that, despite this variation, the fitted values themselves vary little among the different cut-off points (particularly between cut-offs of 50%, 75% and 90%). Therefore, we use 50% as the cut-off point for defining pollock targeting and consequently for including data in the standardization.

The correlation between pollock catch and %Pollock was low (for example 0.29 in 1995) but statistically significant due to a large number of observations (over 10 000). Fig. 5 indicates that when %Pollock is low, the total catch is likely to be low. However, when %Pollock is high, the pollock catch can be anywhere from low to high.

2.3.2 Explanatory variables

The term %Pollock^2 was included most frequently in the most parsimonious model over all years and stratifications (Table 5). The time at which the haul was taken was included in most models for 1998 but in less than half of the models for 1999. The relative importance (the number of times they were included in the final model) of the remaining factors was (in descending order): %Pollock, Speed, Speed*%Pollock, and Speed^2.

There were major differences in model coefficient values among strata as illustrated by a wide range of outliers and relatively small interquartile range (Fig. 6). Parameter estimates indicate a broad range of possible values for the coefficients related to %Pollock and Speed^2, and moderate ranges for the coefficients related to Speed, %Pollock^2 and the interaction term. The categorical variables vessel ID and Day tended to be less variable (Fig. 7). The signs of the Day factor (Table 6) were mainly positive for hauls during daytime; hence a generally lower CPUE occurred during the night. The vessel ID coefficients tended to be positive (Table 6) but negatively skewed (Fig. 7), indicating that some vessels were much less efficient than the remainder. The coefficients related to %Pollock and Speed tended to be negative while the coefficients for the rest of the terms tended to be positive (Speed^2 only moderately so) (Table 6).

Fig. 8 shows the response surfaces for all of the final models for the 1995 federal reporting area strata to illustrate the types of response surfaces obtained. These surfaces were computed using the %Pollock and Speed factors, their squares, and interaction. The categorical factor vessel ID is omitted which centers the response around the average ln CPUE value. The surfaces with no change in the vertical response axis as a function of the factor coefficients indicate a model where only the intercept is significant and %Pollock, Speed, their interactions and quadratic functions were not important (e.g., area / season stratum 519B). A main effect alone leads to a straight-line non-zero slope. Six models include at least one main effect (509A, 509B, 517B, 521B, 541A and 542A). However all models except 519B included either the interaction term, which causes a twisting of the surface (e.g., 521B and 542A) or a quadratic term, which imparts a curvature to the surface. The curvature induced by quadratic terms can be very subtle, resulting in a response surface that appears to have only a main effect (e.g., 517A, 524B). In other situations, quadratic terms dominate a main effect and lead to severe curvature (strata 509B, 517B and 541A). All but three of the graphs include quadratic terms, but curvature is plainly visible in only the graphs for strata 509B, 517B and 541A.

Some general trends of the response surfaces existed across all stratifications, 153 in total. CPUE increased over the entire range of %Pollock in 63 of the 65 response surfaces with slopes that stayed consistently either positive or negative over the entire surface. U-shaped surfaces are caused by a negative linear and a positive quadratic term (see, for example stratum 509B in Fig. 8). 56 of the 153 graphs are U shaped with respect to the %Pollock factor. In 52 of these, the slope is not negative in the vicinity of 90-100 %Pollock, where 80% of the available data lie. With respect to the factor Speed, of those surfaces with a consistent slope over the entire surface, 19 were positive and 14 were negative. Nearly 99% of the hauls are taken at a speed of 3 knots or above. Ten surfaces were such that part of the graph had a positive slope and part had a negative slope due to the interaction term. Generally, slopes are moderated and positive in the area of high speed and high %Pollock where most of the data are (see, for example, the response surface for stratum 521B in Fig. 8.

2.3.3 Post-hoc analysis and stratification

On average, the stratification procedure removed 23% of the variability across all area / season strata, while 55% of the variability in the CPUE data is accounted for by stratification and standardization (Table 7).

The relationship between the vessel ID coefficient and vessel characteristics differed depending on whether the vessel ID coefficients were calculated from the ADF&G or the federal stratifications (Table 8). With the federal stratification, vessel length, and vessel type were significant factors, each with positive coefficients. The lack of significance of two of the three size factors is not surprising, because length, net weight, and horsepower are expected to be correlated. With the ADF&G stratification, all four factors and their squares were significant. Here, the net weight and square of length had negative coefficients. The smaller size of the ADF&G areas likely removed some variation that the federal areas did not, making it easier to identify factors that are statistically significant. In addition, the ADF&G data set is larger because vessels necessarily fish in more of the smaller ADF&G areas than in larger NMFS area, providing for more "observations". When the vessel ID coefficients are plotted against each of the four factors for the 1995 ADF&G strata, there is a positive relationship with the continuous factors and higher CPUE for the inshore catcher vessels relative to the offshore catcher processors (Fig. 9).

2.4. Discussion

2.4.1 General model

The spatial stratifications using the federal areas were based on more data than the ADF&G areas, because they are larger. These larger data sets tend to identify more factors as being statistically significant; hence, the most parsimonious models based on the federal areas had more factors than the relatively data-poor ADF&G stratifications. However, relationships between vessel ID coefficients and vessel characteristics were more significant using the ADF&G areas. The difference between the two stratification schemes may be a statistical artifact as opposed to an important biological difference, however, because one can always find statistically significant differences given a large enough data set. Here we used the standard (though arbitrary) α=0.05 level of significance. Nevertheless, these results show that explaining pollock CPUE as a function of other variables depends on the spatial scale of analysis.

The explained variances in Table 2 are much higher than the 12.7% obtained by Allen and Punsley (1984) but much less than the 63% obtained by Goñi et al. (1999) who also found the percentage of variability explained to be quite variable across species. The percentage of the variability explained in this study ranges from 20-70% over all stratifications while the average over areas for a given year ranges from 36-48% (Table 2), which lies in the middle of the range for other studies. Given that the number of parameters in our models is relatively high due to the large number of factor levels for the vessel ID factor, we expected to explain a high percentage of the variability. Megrey (1986) performed a standardization on the Japanese fleet fishing pollock in the Gulf of Alaska from 1973 to 1983. Using year, quarter, area, trawler type and vessel size, 58% of the total variance was explained by Megrey's model, which is generally greater than in this study. Given that the pollock fisheries of 1995-1999 and those of Megrey (1986) should not be markedly different; the difference is probably due to our stratification by spatial and temporal factors, which removed substantial amounts of the variability. Table 7 indicates an average 23% reduction in variability due to the area / season stratification alone. The effects of the area / season stratification and linear model combine to account for an average of 55% of the variability, very similar to the result of Megrey (1986).

We believe that the use of the %Pollock factor is justified. Strictly speaking, the use of dependent and independent variables that are functions of a common variable may result in overstated confidence in the model results. However, while the correlation between pollock catch and %Pollock is statistically significant, it is fairly low and shows that %Pollock contains other information than that contained in the magnitude of the catch of pollock and worthy of inclusion in the model.

We also believe that restricting the analysis to hauls for which pollock make up at least 50% of the catch in weight is justified. It is important to eliminate those hauls not targeting pollock because harvesters are not fishing in parts of the water column where pollock are principally located, and inclusion of these hauls would result in substantial underestimation of the pollock biomass, particularly if there are large numbers of low percentage-of-pollock hauls. If the majority of a haul by weight is pollock, then it is reasonably safe to assume pollock was the target (Galen Tromble, NMFS, pers. comm.); hence a greater than 50% threshold is the most logical point for the targeting criteria. It can be argued that the threshold should be above 50% (of the hauls with 50% pollock or more, 80% contain at least 90% pollock) due to the unusually low bycatch of the pollock fishery. However, the sensitivity analysis does not indicate that the cut-off has much effect on the fitted values, which are of primary interest in this study. If one were specifically interested in characterizing the fishery though, better information about targeting would be necessary for useful results.

2.4.2 Explanatory variables

We expected to see an increase in CPUE with the percentage of pollock caught in a haul, and this expectation is partially validated in Fig. 4. Given the same amount of time hauled and a total haul weight, a vessel with a greater percentage of pollock in the catch would have a larger CPUE. We also expected to see an increase in CPUE with vessel speed because more area would have been covered in less time and the fish could have been outrun at higher speeds. However, many response surfaces indicated negative slopes with increasing speeds. Lower CPUE at higher speeds could be due to increased noise and net-induced water turbulence, or increased by-catch. In addition, boats will have different optimal tow speeds depending upon the exact combination of gear used and depth at which the targeted school resides, as slower speeds will cause a lower haul depth. Thus, speed-related factors would not necessarily be linearly related to catch, because speed may have less to do with catchability, within an effective range of speeds, and more to do with depth-related targeting. Hence, the response surfaces differ by area and the lack of a consistent trend suggests that the relationships with speed and %Pollock may not be causal. A causal mechanism is not required for this study, however, because its purpose is to standardize for the effects of these variables. Rather, it is important to remove any effects that are coincident with those variables.

The Day factor was found to be quite important in 1998 and, given the diel behavioral of pollock, is not surprising. Pollock tend to be tightly schooled during the day and spread out much more evenly throughout the water column at night for feeding (T. Honkalehto, NMFS pers. comm.), which would substantially change their catchability. Given the fish-detecting ability aboard modern vessels, targeting the dense schools during the day would make for increased CPUE and indeed the day factor tends to have positive coefficients while those for night are negative. The Day factor was not as important in 1999 as we expected and possible causes for this remain speculative.

We found that vessel ID accounted for the majority of the explained sum of squares, because of the large number of individual vessels. We expected this because variation in CPUE is primarily dependent upon vessel characteristics, which the vessel ID variable wholly accounted for. Large (1992) found similar results in his model using individual vessels with the vessel factor explaining the largest percentage of the variability, about 20%. In our models the vessel factor explained about 29% of the variation on average (Table 2). In general, our method allowed for specific individual vessel level adjustments to explain the greatest amount of variance as possible. The trade-off is that interactions including vessel ID as a factor, and characterization of the fishery in more general terms, such as using the effect of vessel size, was possible only by post-hoc analysis.

The high values of the response in some of the graphs exceeded 10 and the lowest values were less than –10 (see, for example, stratum 542A in Fig. 8), whereas fitted values of ln CPUE do not vary nearly this much (e.g., Fig. 10). The range of the explanatory variables in the graph may be outside the data range, or the vessel ID coefficients have a stabilizing effect on the fitted values. It is likely that some coefficients are artificially large due to vagaries in the data, creating the large skews seen in the box plots. Large deviations of two factors working in opposite directions could occur due to multicollinearity. Indeed, all coefficient values in a model are extreme when any one of them is. Because vessel ID explains so much of the variability, the other factors may be working more as model fitting variables with less biological meaning, resulting in less variation in fitted values than in model coefficients.

2.4.3 Post-hoc analysis and stratification

Typically, a single model is applied to the entire data set when standardizing catch and effort data so that the predicted CPUE is directly comparable across the entire fishery. Thus, the stratification by year, area, and season in our study would be replaced with year, area and season as factors in the single model. While our stratification resulted in standardized CPUE values readily applicable to DeLury depletion estimators, the procedure greatly increased the amount of work and would not be suitable for use as an index of abundance in standard stock assessments. A middle ground between these two approaches would be to use random effects models to share estimation of model coefficients among strata. We intend to pursue random effects models in subsequent work.

The post-hoc analysis on the vessel characteristics indicates that CPUE increases as the vessel gets larger and more powerful, as expected. However, the significance of the vessel-type factor suggested that the smaller inshore catcher vessels were more efficient than the larger offshore catcher-processors after adjusting for size. This is not to say that an 18-meter catcher vessel would have higher CPUEs than a 76-meter catcher processor, because the primary trend is for vessels to have higher catch rates as size increases. However, of two vessels the same size, a catcher vessel would be expected to produce slightly higher CPUEs. We might expect this result because the catcher vessels focus only on catching fish while the processors must balance efficiency in catching with efficiency in processing the catch such that high CPUEs are not the only goal of the vessel (Dorn, 1998). While these post-hoc regression analyses are highly significant, they do not explain much of the associated variability, which provides further motivation for utilizing the Vessel ID numbers directly in the standardization instead of general vessel characteristics.

2.4.4 Concluding remarks

The measure of fishing effort was the haul time of the trawl. A more accurate measure of effort would include search time (Mangel and Beder, 1985); unfortunately no measure of search time is recorded in the observer database. Hence, with a schooling fish such as pollock and fish-finding technology, CPUE is likely to be hyperstable. The degree of hyperstability will also change according to season as the percentage of the 24 hour period under darkness radically shifts in higher latitudes and the time spent in schools (day) or dispersed throughout the water column (night) changes (T. Honkalehto, NMFS, pers. comm.). For stock assessment, hyperstability, if not corrected for, would result in a higher estimated biomass. For our purposes, a hyperstable biomass will effectively increase our type II error rate in our DeLury depletion estimators so our findings will err on the conservative side.

The stratification procedure proved to be an effective means of eliminating variability and meeting GLM assumptions, but left the standardizations incomparable across stratifications. The use of the vessel ID number as a factor provided a high degree of explanatory power with the drawbacks of large numbers of parameters, and no ability to characterize the fishery in more general vessel-related terms. The use of vessel-specific factors may have also reduced the biological meaning of the remaining factors. However, analysis of the vessel ID coefficients did provide insight into the characterization of the fishery. Finally, the use of response surface analysis provides for a big-picture perspective on the effects of the GLM not easily seen by examination of the independent factor coefficients.

2.4.5 Acknowledgments

The authors wish to thank Mike Sigler, Milo Adkison, Brendan Kelly and Gordon Kruse for their helpful advice. Comments by David B. Sampson and an anonymous reviewer led to a much improved paper. This publication is the result of research sponsored by Alaska Sea Grant with funds from the National Oceanic and Atmospheric Administration Office of Sea Grant, Department of Commerce, under grant no. NA 86RG0050 (project no. R/101-01) and from the University of Alaska with funds appropriated by the state.

2.5 References

ADF&G (Alaska Department of Fish and Game), 2001. ADF&G Chart Series, Bering Sea 2001. <http://www.cf.adfg.state.ak.us/geninfo/statmaps/charts.htm> Accessed March 20, 2003.

Allen, R., Punsley, R., 1984. Catch rates as indices of abundance of yellowfin tuna *Thunnus albacares* in the eastern Pacific Ocean. Int.-Amer. Trop. Tuna Comm. Bull. 18, 301–379.

Bannerot, S.P., Austin, C.B., 1983. Using frequency distributions of catch per unit effort to measure fish stock-abundance. Trans. Amer. Fish. Soc. 112, 608–617.

DeLury, D.B., 1947. On the estimation of biological populations. Biometrics 3, 145–167.

Dorn, M.W., 1998. Fine-scale fishing strategies of factory trawlers in a midwater trawl fishery for Pacific hake (*Merluccius productus*). Can. J. Fish. Aquat. Sci. 55, 180–198.

Dunn A., Harley, S.J., Doonan, I.J., Bull, B., 2000. Calculation and interpretation of catch-per-unit-effort (CPUE) indices. N. Z. Fish. Ass. Rep. 2000/1.

Fox, D.S., Starr, R.M., 1996. Comparison of commercial fishery and research catch data. Can. J. Fish. Aquat. Sci. 53, 2681–2694.

Goñi, R., Alvarez, R., Adlerstein, S., 1999. Application of generalized linear modeling to catch rate analysis of Western Mediterranean fisheries: the Castellón trawl fleet as a case study. Fish. Res. 42, 291–302.

Harley, S.J., Myers, R.A., Dunn, A., 2001. Is catch-per-unit-effort proportional to abundance? Can. J. Fish. Aquat. Sci. 58, 1760–1772.

Hilborn, R., Walters, C.J., 1992. Quantitative Fisheries Stock Assessment: Choice, Dynamics and Uncertainty. Chapman & Hall, New York.

Ianelli, J.N., Bardeaux, S., Honkalehto, T., Walters, G., Williamson, N., 2002. Eastern Bering Sea walleye pollock assessment. NPFMC Bering Sea/Aleutian islands Stock Assessment and Fishery Evaluation, Seattle, WA. pp. 33–120.

Large, P. A., 1992. Use of a multiplicative model to estimate relative abundance from commercial CPUE data. ICES J. Mar. Sci. 49, 253–261.

Mangel, M., Beder, J.H., 1985. Search and stock depletion: Theory and applications. Can. J. Fish. Aquat. Sci. 42, 150–163.

MathSoft, 1999. S-Plus 2000 Guide to Statistics, Vol. 1. Data Analysis Products Div., Seattle, WA.

Megrey, B.A., 1986. Estimation of relative pollock abundance on a fishing power analysis of the Japanese foreign fishery in the Gulf of Alaska. In: M. Alton (Ed.), A workshop on comparative biology, assessment and management of Gadoids from the north Pacific and Atlantic oceans. Northwest and Alaska Fisheries Center, Seattle, WA. pp. 553–584.

Milliken, G.A., Johnson, D.E., 1984. Analysis of Messy Data. Volume I: Designed Experiments. Lifetime Learning Publications, Belmont, CA.

NOAA (National Oceanographic and Atmospheric Administration) NMFS, Alaska Region, 2002. 2003 Record keeping and Reporting (R&R) – Figures, BSAI Statistical and Reporting Areas, 2002. http://www.fakr.noaa.gov/rr/figures.htm Accessed March 20, 2003.

NRC (National Research Council), 2000. Improving the Collection, Management, and Use of Marine Fisheries Data. National Academy Press, Washington, D.C.

Pelletier, G.J., 2003. Sunrise, sunset, solar position, and solar radiation calculators for Excel. http://users.vei.net/pelican/sunrise.html Accessed July, 2003.

Punsly, R.G., Deriso, R.B., 1991. Estimation of the abundance of yellowfin tuna, *Thunnus albacares*, by age groups and regions within the eastern Pacific Ocean. Int.-Amer. Trop. Tuna Comm. Bull. 20, 99–131.

Quinn, T.J. II., 1987. Standardization of catch-per-unit-effort for short-term trends in catchability. Nat. Res. Mod. 1, 279–296.

Quinn, T.J. II, Deriso, R.B., 1999. Quantitative Fish Dynamics. Oxford University Press, New York.

Richards, L., Schnute, J., 1986. An experimental and statistical approach to the question: Is CPUE an index of abundance? Can. J. Fish. Aquat. Sci. 43, 1214–1227.

Rose, G. A., Kulka, D.W., 1999. Hyperaggregation of fish and fisheries: how catch-per-unit-effort increased as the northern cod (Gadus morhua) declined. Can. J. Fish. Aquat. Sci. 56(Suppl. 1), 118–127.

Schnute, J., Mckinnell, S., 1984. A biologically meaningful approach to response surface analysis. Can. J. Fish. Aquat. Sci. 41, 936–953.

Vignaux, M., 1996. Analysis of spatial structure in fish distribution using commercial catch and effort data from the New Zealand hoki fishery. Can. J. Fish. Aquat. Sci. 53, 963–973.

Westrheim, S.J., Foucher, R.P., 1985. Relative fishing power for Canadian trawlers landing Pacific cod (Gadus macrocephalus) and important shelf cohabitants from major offshore areas of western Canada, 1960-81. Can. J. Fish. Aquat. Sci. 42, 1614–1626.

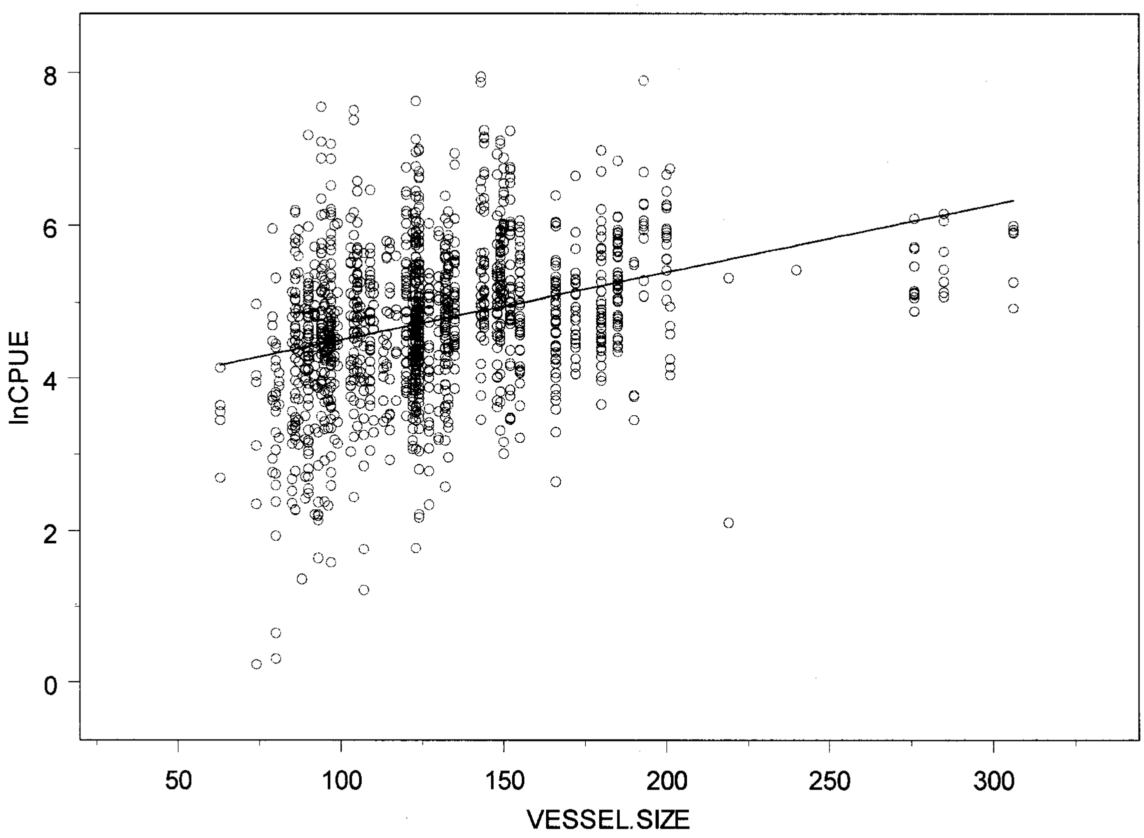


Fig. 2.1. ln CPUE versus vessel size in feet for ADF&G area 655430B in 1995, showing the increase in CPUE with vessel size.

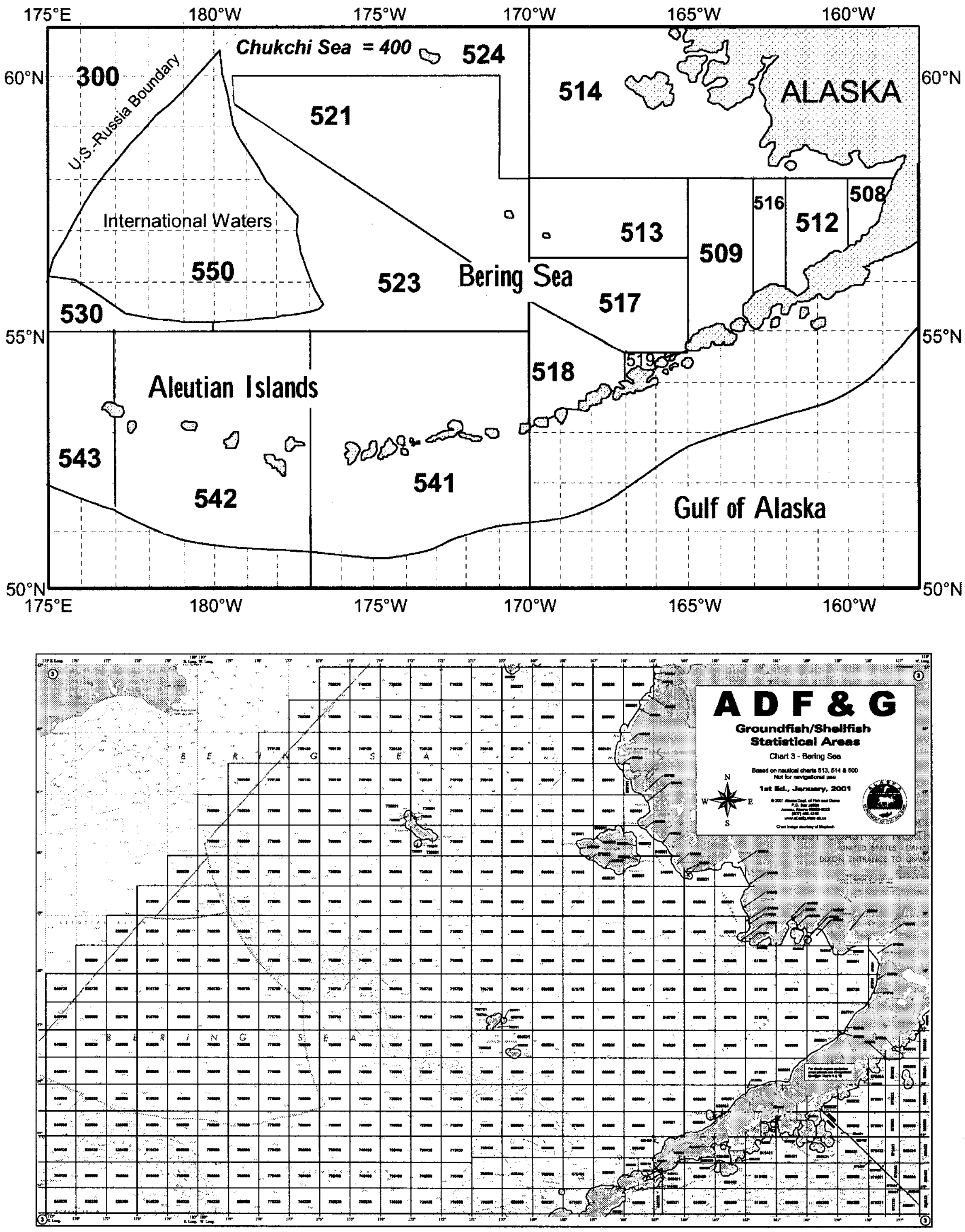


Figure 2.2. Maps of the Bering Sea / Aleutian Islands and Gulf of Alaska showing the federal reporting areas (NOAA, 2002) and the ADF&G reporting areas (ADF&G, 2001).

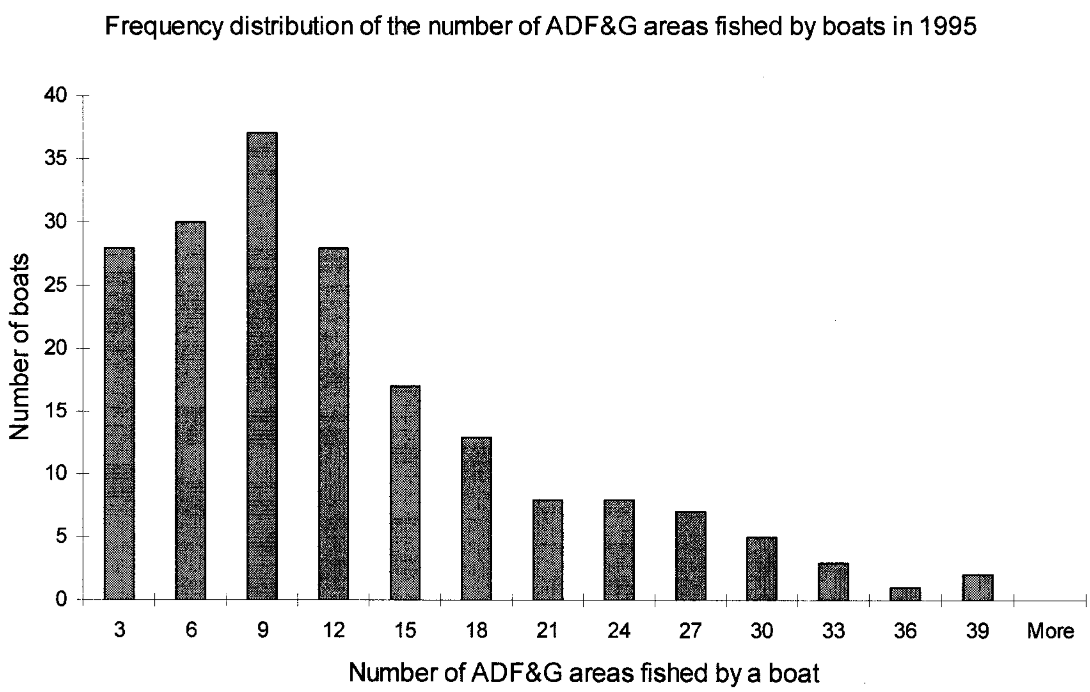


Fig. 2.3. Histogram of the number of ADF&G reporting areas fished by a boat in 1995.

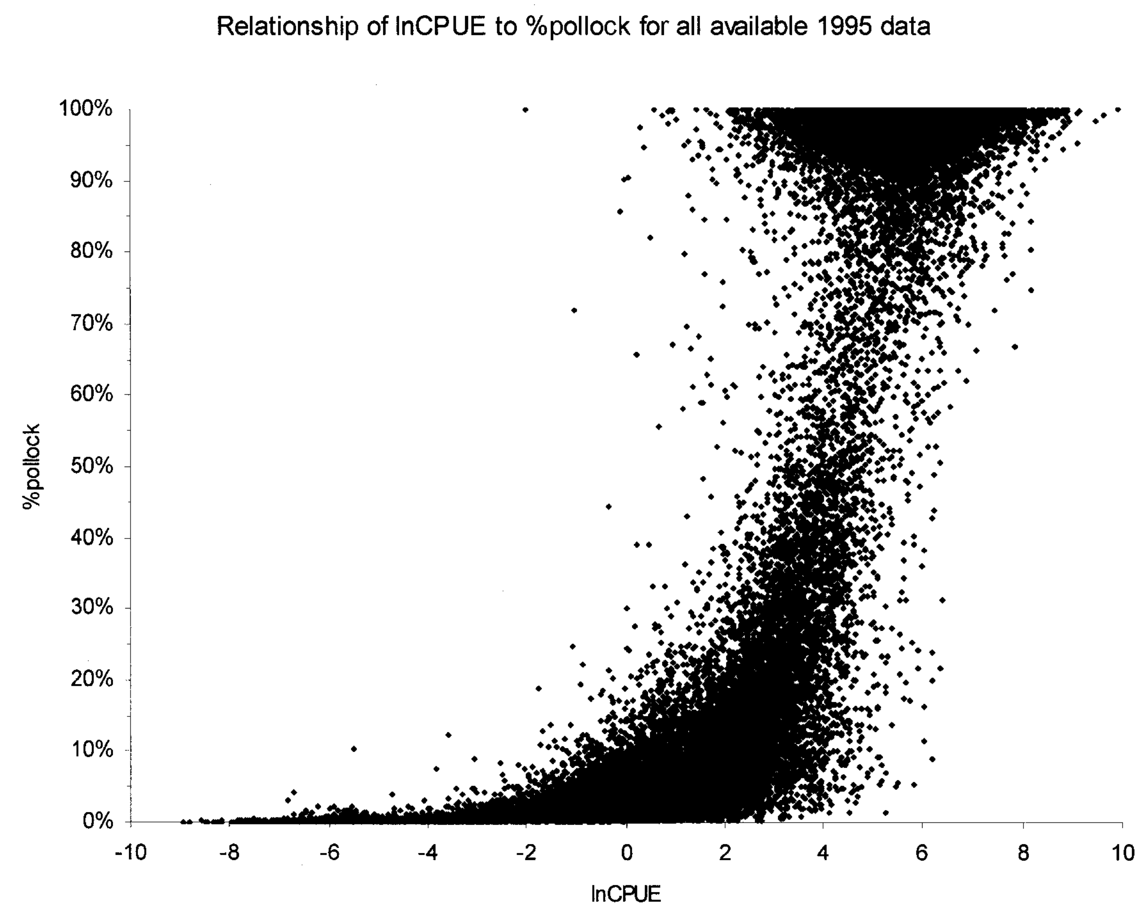


Fig. 2.4. The relationship between ln CPUE and the percentage of pollock in the haul using 1995 data.

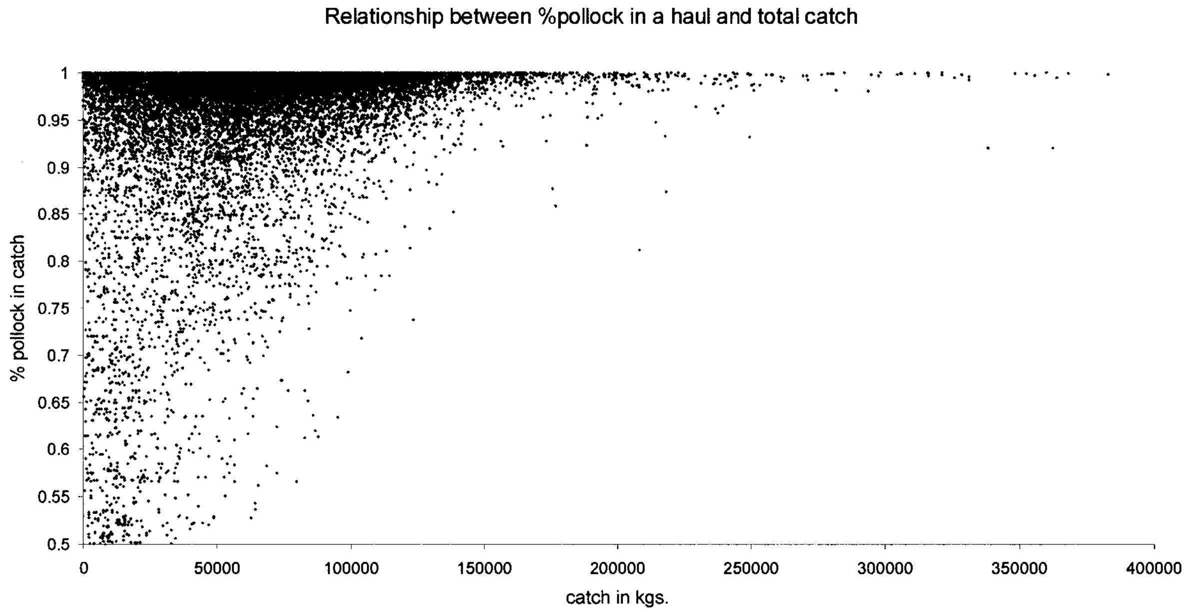


Fig. 2.5. Percentage of pollock in the haul versus haul weight for 1995 (%Pollock > 50% only). Three hauls between 400,000 and 600,000 kg were removed to increase detail.

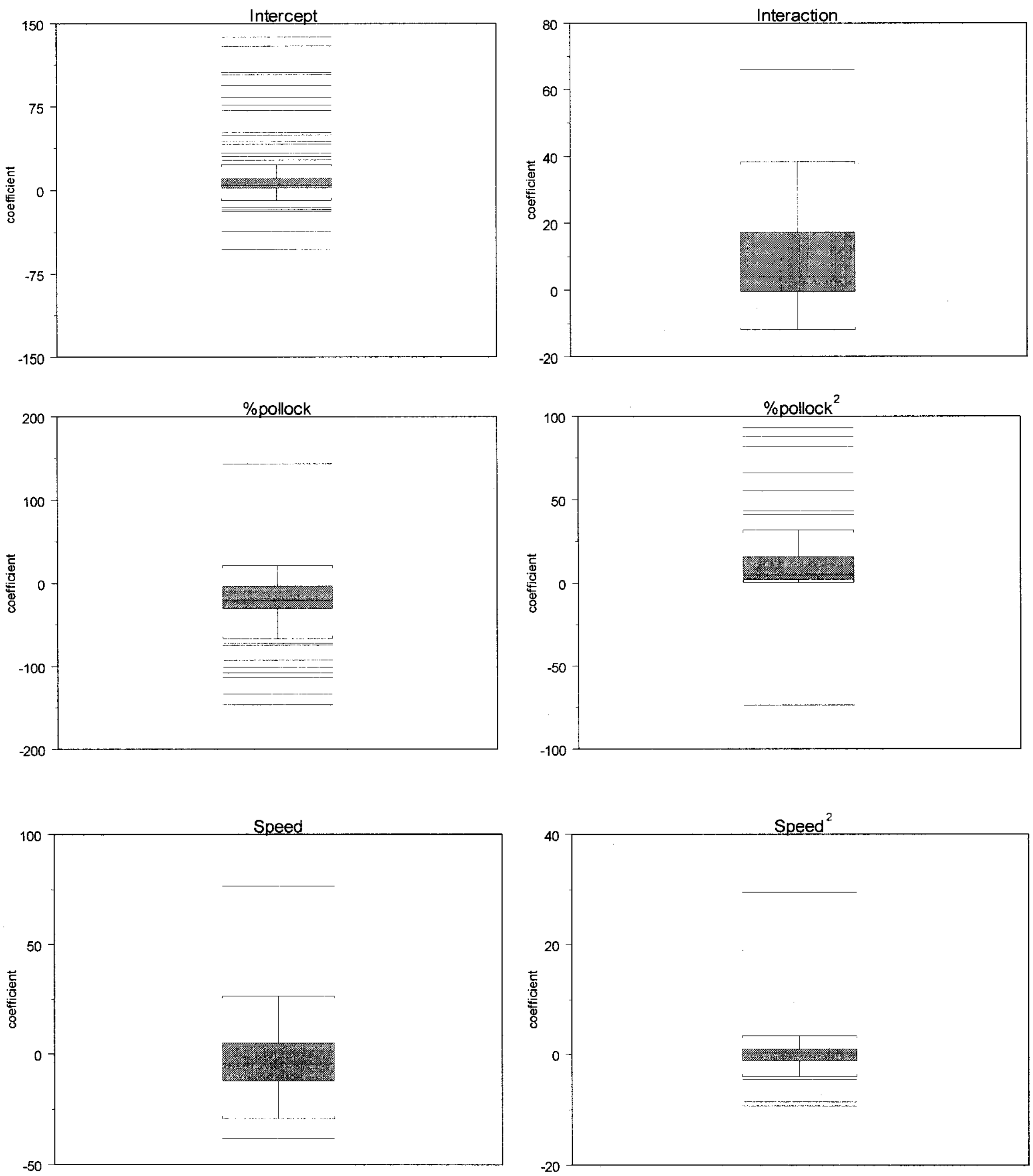


Fig. 2.6. Box plots of factor coefficients aggregated over the analyses for the federal and ADF&G reporting areas. A few outliers were removed from the intercept, speed^2, %Pollock and %Pollock^2 panels to better represent of the bulk of the information.

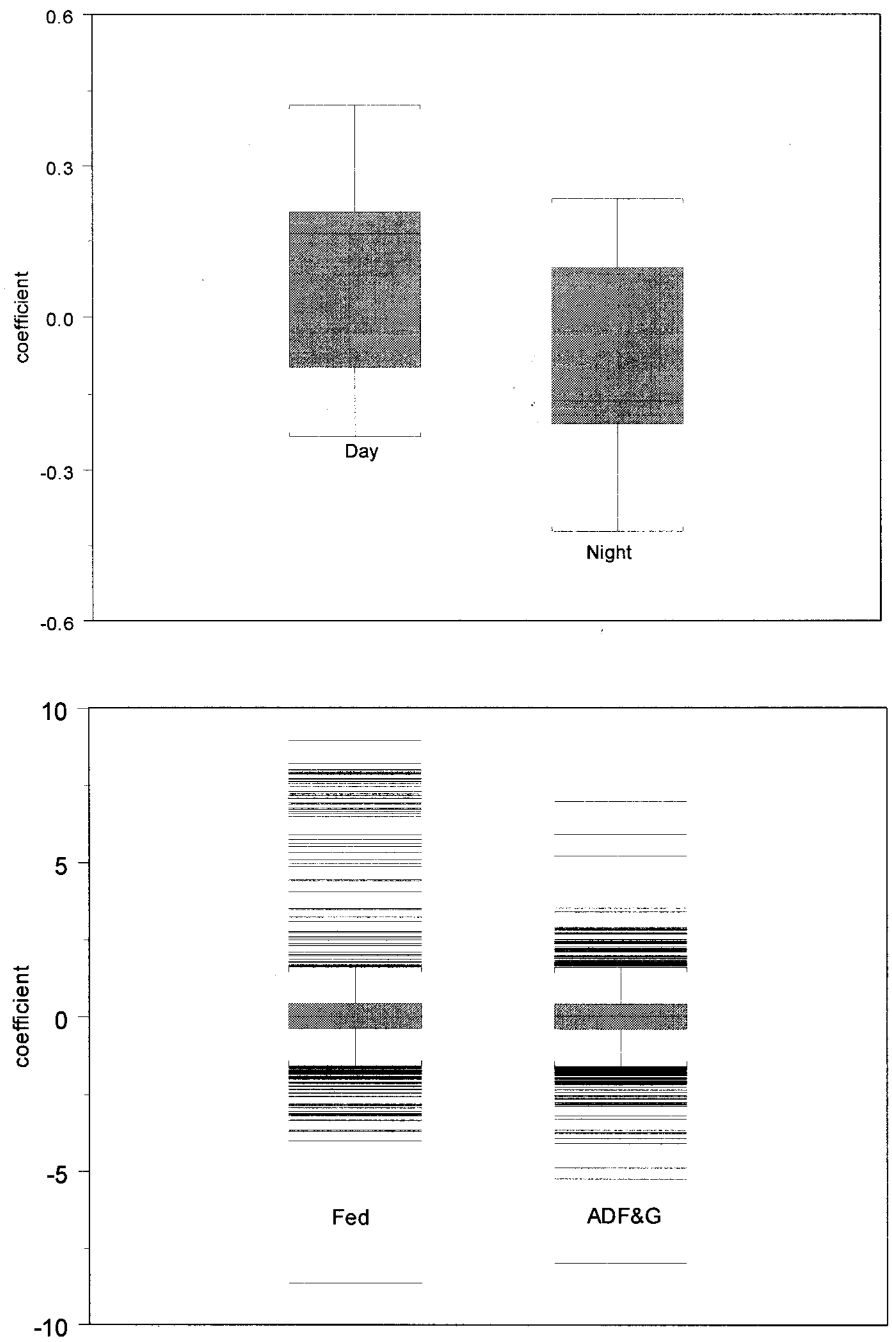


Fig. 2.7. Box plots of vessel ID and Day factor coefficients (upper and lower panels respectively). Results are shown separately for the ADF&G and federal reporting areas. Outliers of -231 (federal stratification) and -43 (ADF&G stratification) are omitted from the upper panel for improved clarity.

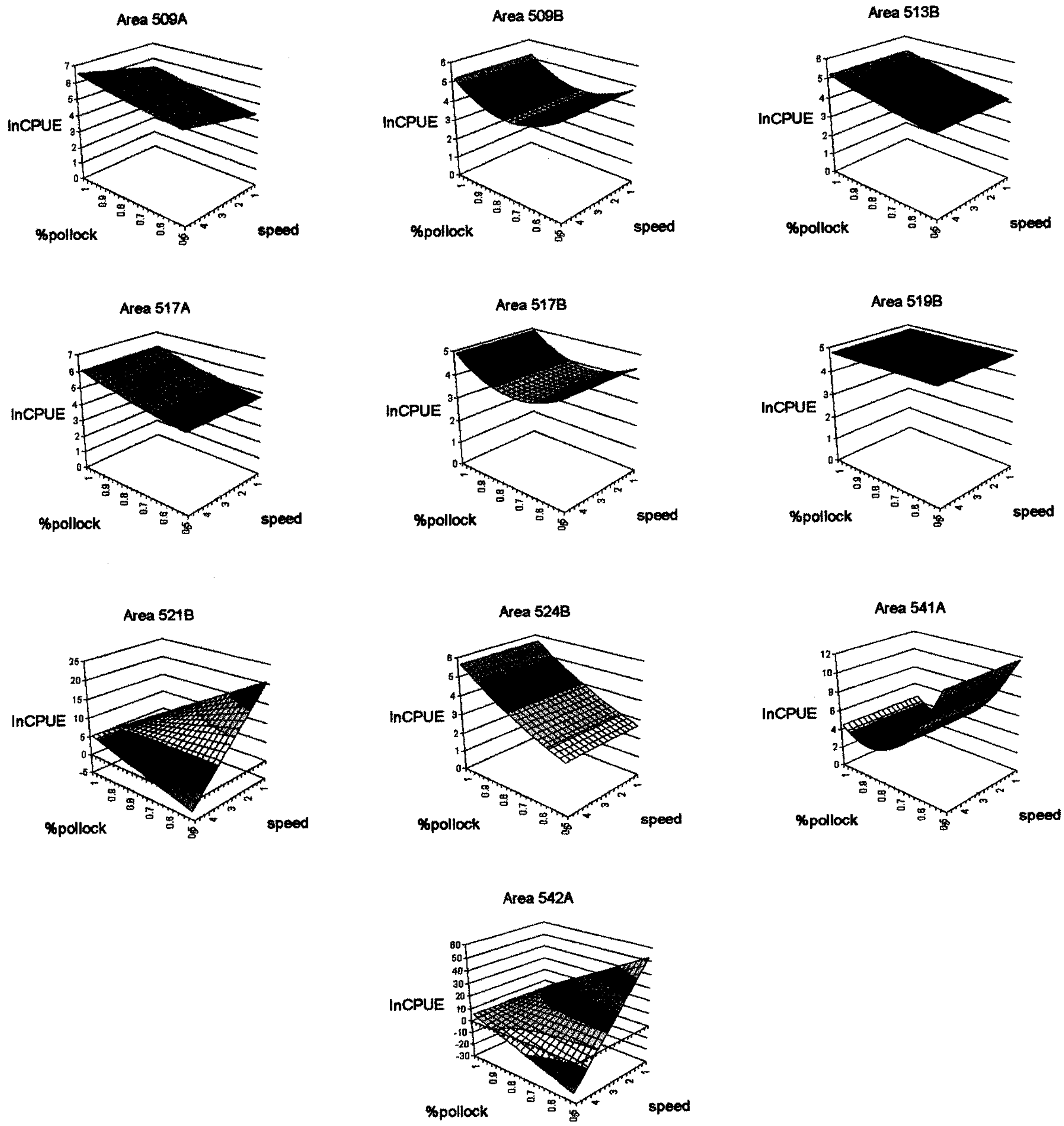


Fig.2. 8. Response surface graphs for the 1995 federal reporting areas.

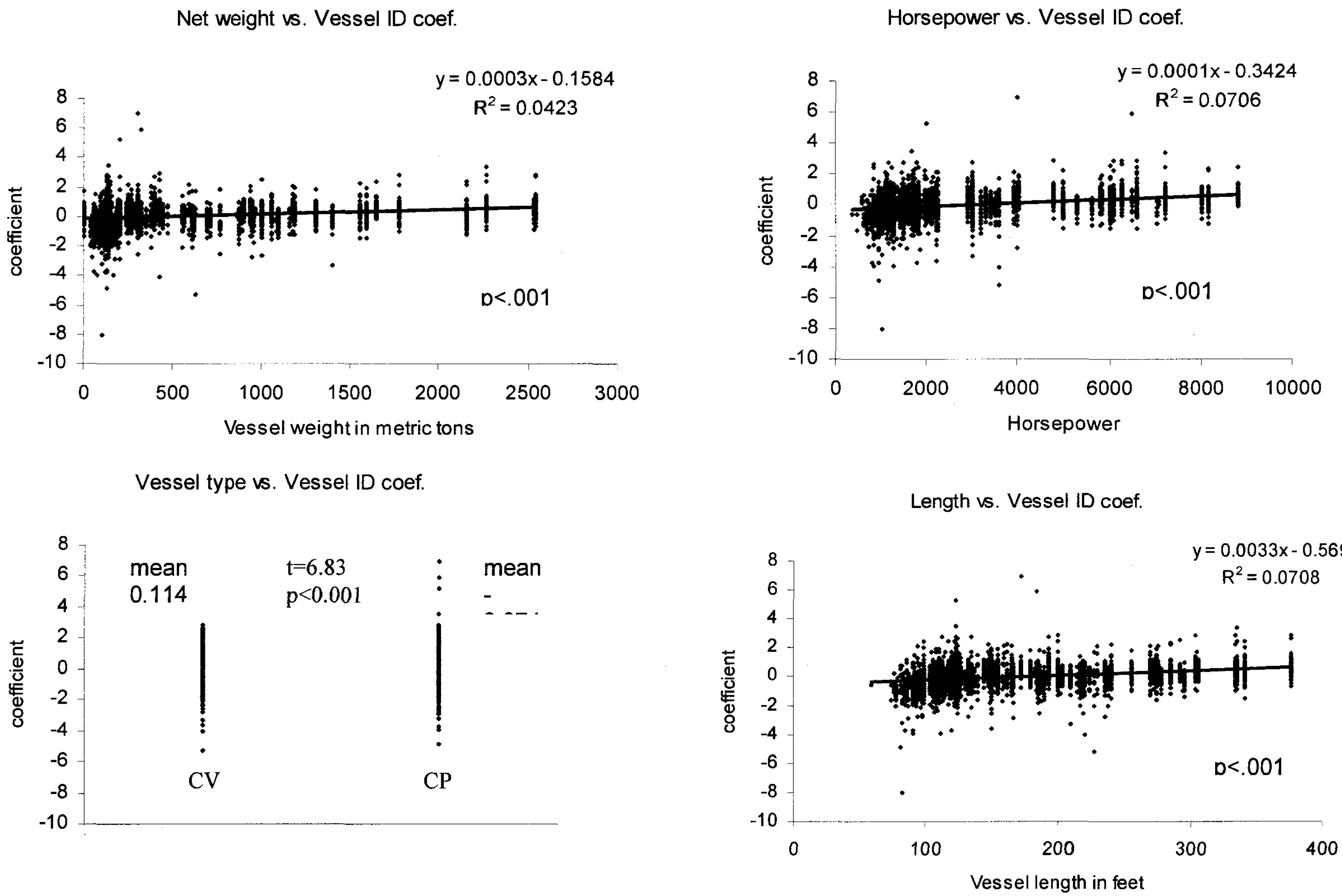


Fig. 2.9. Vessel ID coefficients versus vessel weight, vessel type, horsepower, and vessel length.

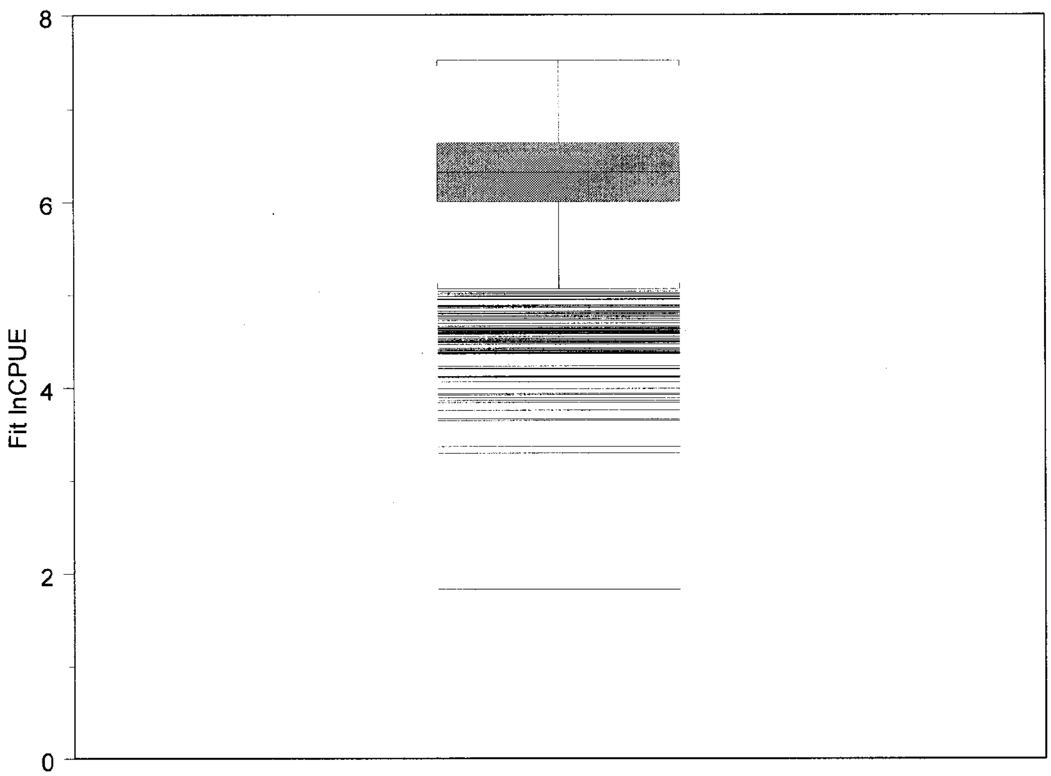


Fig. 2.10. Box plot of the predicted ln CPUE for federal area/season 509A in 1995.

Table 2.1. The tonnage of pollock and the number of hauls available for standardization after removal of catch data for the three reasons listed in text.

Year	1995		1996		1997		1998		1999	
	Kg	Hauls	Kg	Hauls	Kg	Hauls	Kg	Hauls	Kg	Hauls
Total pollock catch	1,387,536	56,522	1,263,541	60,809	1,209,738	59,271	1,216,817	53,836	1,051,034	45,586
Elimination reasons										
Off season	123,724	27,519	124,941	29,630	132,856	32,730	95,941	24,833	100,677	19,951
Pollock non target	25,960	12,167	105,006	13,744	114,267	12,563	128,463	12,835	128,640	15,154
No haul duration or vessel speed data	199,888	1,089	93,514	569	87,911	577	120,405	1,338	116,578	1,419
Available data	1,037,965	15,747	940,080	16,866	874,704	13,401	872,008	14,830	705,139	9,062
Percent of total	75%	28%	74%	28%	72%	23%	72%	28%	67%	20%

Table 2.2. Average percentage of the total sum of squares (SSQ) explained by the standardization procedure, along with the average proportion of the total explained SSQ for each factor using Type III SSQ calculations.

Year/Area	Average explained	Vessel ID	Speed	Speed^2	Percent pollock	Percent pollock^2	Interaction	Day
95ADF&G	41.7	30.5	0.5	1.7	2.3	3.1	2.0	
95fed	39.8	30.6	2.3		2.5	2.5	3.4	
96ADF&G	43.4	27.2	0.7	0.9	2.7	4.9	4.2	
96fed	36.9	26.0	1.7	0.9	0.7	1.0	2.7	
97ADF&G	48.8	40.2	1.7	1.9	4.5	4.0		
97fed	39.8	28.3	2.3	2.5	0.8	2.4	3.0	
98ADF&G	44.5	26.3	1.4		2.5	6.5	1.6	5.3
98fed	39.0	27.3	0.7	0.3	0.6	2.5	0.7	2.7
99ADF&G	46.7	32.7	2.5	0.8	2.9	4.4	2.7	5.4
99fed	43.9	27.5	3.9	2.2	3.2	4.1	2.8	2.3
Mean	42.4	29.7	1.8	1.4	2.3	3.6	2.6	3.9

Table 2.3. Sensitivity of the coefficient values from the standardization based on the data for ADF&G area 645501 season A in 1994 to the %Pollock cut-off point.

%Pollock	Intercept	Speed	$Speed^2$	%Pollock	$\%Pollock^2$	Interaction
0-100	1.40			7.98	-4.02	0.26
50-100	3.81	0.23		1.76		
75-100	18.72	0.22		-32.93	19.92	
90-100	105.81	0.18		-213.98	114.08	

Table 2.4. Sensitivity of the value of ln CPUE predicted for various combinations of %Pollock and speed to the %Pollock cut-off point.

Speed	Cut-off	%Pollock		
		0.9	0.95	1
Low	0	5.79	5.85	5.88
2	50	5.85	5.94	6.03
	75	5.66	5.85	6.15
	90	5.99	5.85	6.27
Mean	0	6.22	6.29	6.35
3.805851	50	6.27	6.36	6.45
	75	6.06	6.25	6.55
	90	6.32	6.17	6.60
High	0	6.73	6.83	6.92
6	50	6.77	6.86	6.95
	75	6.54	6.73	7.03
	90	6.71	6.57	6.99

Table 2.5. The percentage of times each factor was included in the most parsimonious model for each combination of year and area stratification. Total counts for each factor are summed separately for 1995-1997 and 1998-1999.

	Speed	Speed^2	%Pollock	%Pollock^2	Interaction	Day
1995 ADF&G	21%	16%	37%	74%	16%	
1995 fed	30%	0%	50%	70%	10%	
1996 ADF&G	10%	15%	55%	80%	10%	
1996 fed	10%	20%	80%	90%	10%	
1997 ADF&G	5%	5%	37%	58%	0%	
1997 fed	36%	18%	45%	73%	18%	
1995-1997 totals	15	11	43	65	9	
1998 ADF&G	30%	10%	30%	70%	20%	70%
1998 fed	33%	11%	56%	89%	22%	89%
1999 ADF&G	19%	10%	57%	48%	19%	24%
1999 fed	25%	17%	50%	83%	25%	33%
1998-1999 totals	16	7	29	42	13	31

Table 2.6. Signs of the coefficients for each of the factors. Results are shown for both levels of the Day factor. The results for the vessel ID factors are summed over all levels.

Continuous

	Intercept	Speed	Speed^2	%Pollock	%Pollock^2	Interaction
Negative	20	18	8	56	1	7
Positive	131	13	11	15	107	17

Categorical

	Day	Fed Vessel ID	ADF&G Vessel ID
Negative	8	1666	2659
Positive	23	1752	2876

Table 2.7. Comparison of explained variability due to stratification and standardization.

Year/Area	Unstratified TSS	Stratified TSS	Variability explained due to stratification	% Variability explained due to stratification	Standardization ESS	% total variability explained
95ADF&G	13445	9704	3741	28%	3897	57%
95fed	18114	13455	4658	26%	5138	54%
96ADF&G	12211	10301	1911	16%	4150	50%
96fed	16530	15331	1199	7%	6425	46%
97ADF&G	11914	8297	3617	30%	3742	62%
97fed	16250	11429	4821	30%	4422	57%
98ADF&G	13344	7919	5425	41%	3534	67%
98fed	17478	11697	5781	33%	4431	58%
99ADF&G	4961	4350	611	12%	1865	50%
99fed	9461	8527	934	10%	3409	46%
Mean				23%		55%

Column 2 shows the total sum of squares (TSS) from a model with no stratification. Column 3 shows the TSS summed across strata using the same data as column 2. Column 4 is the difference between columns 3 and 2 and column 5 is the ratio of column 4 to column 2 expressed as a percentage. Column 6 shows the explained sum of squares (ESS) due to the standardization model summed across strata. Column 7 is the percentage of variability in column 2 explained by stratification (column 4) and the standardization model (column 6).

Table 2.8. Relationship between vessel ID factor and various vessel characteristics. Results are shown separately for the ADF&G and federal reporting areas.

	ADF&G		Fed	
	Value	Pr(>|t|)	Value	Pr(>|t|)
Intercept	-2.13E+00	p<0.001	-2.19E+00	p<0.001
Length	1.24E-02	p<0.001	5.83E-03	p=0.015
Net weight	-5.66E-04	p<0.001		
Horsepower	1.56E-04	p<0.001	1.10E-04	p=0.147
Vessel type	2.14E-01	p<0.001	3.96E-01	p<0.001
Length^2	-1.84E-05	p<0.001		
Net weight^2	2.00E-07	p<0.001		
Horsepower^2	0.00E+00	p=0.014		

CHAPTER 3

A DeLury depletion estimator for walleye pollock (*Theragra chalcogramma*) in the eastern Bering Sea[3]

Brian C. Battaile and Terrance J. Quinn II

ABSTRACT

Concerns about local depletion of fish populations are intensifying, as interest becomes focused on finer spatial and temporal scales. The DeLury model was used to investigate local depletion of the eastern Bering Sea walleye pollock population by its fishery by using spatial and temporal scales thought to meet assumptions about closure and applicability. Local depletion is estimated as the slope of logarithmic catch-per-unit-effort (CPUE) from the fishery versus cumulative effort, with data from 1995-1999 stratified by small areas, short seasons and years. Of 237 depletion estimators, 172 had negative slopes, 94 of which were significant, a greater number than would be expected by chance alone. Of the 65 positive slopes, 19 were significantly positive, which is also more than would be expected. Cumulative depletion over a season was inversely related to estimated initial biomass, total catch, and total effort, indicating that depletion is detected more easily in areas of low abundance and consequently lower catch and effort. Our fine-scale estimates of depletion are much smaller than the overall depletion from annual stock assessments, showing that commercial data alone can be at best a spatiotemporal index of depletion. This hyperstable relationship may result from the lack of search time in the measure of effort. Evidence also suggests that measures that were

---

[3] Submitted to Natural Resource Modeling

taken starting in 1999 to disperse the exploitation pressure in space and time may decrease local depletion, and that pollock may repopulate an exploited area in a relatively short time period (weeks).

3.1 INTRODUCTION

One paradigm of marine fisheries management has been that annual assessment of fish stocks in aggregate can be used to develop sustainable harvest policies that protect the target fish population. However, as criticism of marine fisheries management has escalated due to management failures (e.g., northern cod), more complex objectives (such as ecosystem protection), and a broadening of interest groups (e.g., the environmental community), there is a need to focus on finer spatial and temporal scales to investigate local effects on targeted fish populations and other components of the ecosystem.

As one example, the biological and economic importance of walleye pollock (*Theragra chalcogramma*) has taken center stage for the Alaskan fishing community, manifesting itself in scientific, environmental, social, and political debate on a national scale (NRC 2003). The eastern Bering Sea pollock population has supported a sustainable annual harvest of approximately 1 million metric tons since the mid-1960's, the largest in US waters (Ianelli 2003). This fishery is supported by the largest single species biomass in the eastern Bering Sea, a biomass that clearly has important ecosystem scale implications. Major declines in the western stock of the Steller sea lion (*Eumetopias jubatus*) have raised concerns that the walleye pollock and other trawl fisheries are at least partially responsible. The National Marine Fisheries Service

(NMFS) has imposed more stringent regulations on the pollock fishery since 1999 to avoid possible impacts on the sea lion stock. To date, there has not been a comprehensive analysis of existing commercial fishery data to address the interactions between sea lions and the pollock fishery. Thus, we examine commercial catch rates of pollock within a spatiotemporal framework to look for variation that might be associated with sea lion declines.

The impetus for further regulation of the pollock fishery in the wake of the Steller sea lion endangered listing is based on the potential for the fishery to cause sufficient local depletion of walleye pollock that sea lions would not get enough food. When nutritional stress was cited as a potential factor in the decline of the sea lion, NMFS determined that the existing pollock fishery would likely jeopardize the continued existence of the Steller sea lion (NRC 2003), despite having no quantitative measurement of local depletion. Management measures were designed to spread out the fishery in space and time and to limit fishery activities in sea lion critical habitat. In addition, the American Fisheries Act (AFA) was authorized in 1999 further changing the regulatory landscape. From 1995-98, the fishery consisted of two seasons, one in the winter and one in the fall, each about one month long. In 1999 the fishery was broken into four seasons, two in the winter, one in late summer and one in the fall, effectively doubling the time allotted to pollock fishing while catch quotas were limited around Steller sea lion critical habitat, though not entirely eliminated. In addition, the AFA rules eliminated much of the derby style race for fish by allowing quotas to be assigned to individual boats (see Appendix A.1 for details on the fishery regulations before and after 1999). Fishery information before and after those changes could provide insight on the effectiveness of these fishery regulations.

Stock assessment of walleye pollock produces annual estimates of population parameters for the entire eastern Bering Sea (Ianelli et al. 2003). A triennial hydro-acoustic survey and a bottom trawl survey in summer provide indices of abundance, which are integrated with annual commercial fishery catch-at-age data. Such stock assessment methodology cannot determine if competition occurs because the temporal and spatial scales are too large. Pollock management is designed to be sustainable over the entire Bering Sea and over the entire year. Competition with sea lions however will occur only during fishing seasons and in areas where Steller sea lions occur, which are relatively small temporal and spatial scales. Hence, the data requirements are much different from those collected by surveys; the only source of information about competition of the appropriate scale comes from observer data from the fishery in the form of daily catch-per-unit-effort (CPUE) information.

Depletion estimation provides the methodology to determine if the fishery is potentially competing with Steller sea lions for food and specifically requires CPUE as its data. DeLury (1947) and Leslie and Davis (1939) developed depletion-based population estimators that are well described in the classical references of Ricker (1975) and Seber (1982). Depletion estimators are used and improved upon throughout the primary literature (Braaten 1969; Polovina 1986; Quinn 1987), where they are typically employed to estimate the initial biomass from a series of removals. Depletion occurs when removals occur faster than immigration and recruitment can replace removed individuals.

Here, we use the DeLury methodology to determine if the fishery-caused reduction of the pollock population during fishing seasons is statistically detectable.

While the very act of fishing must cause some depletion, spatiotemporal scales, biological mechanisms, and random variations in the data can hide the signal, particularly in commercial fishery data. Migration, recruitment, mortality, differences in catchability, pollock biology, vessel characteristics and spatial correlation all work to disguise any depletion signal. Additionally, significant portions of the population typically need to be removed for the depletion signal to be detected. Migration, recruitment, mortality, spatial correlation and catchability differences due to pollock biology can all be mitigated via generalization of the DeLury model or spatiotemporal stratification of the data, while catchability differences due to vessel characteristics can be standardized (see Appendix A.2 for further discussion on this in relation to the DeLury assumptions).

3.2 MATERIALS AND METHODS

3.2.1 Mathematical model

Three assumptions of the data are required of the DeLury method: (1) The population is closed, or if not closed all population changes are known, (2) each individual has an equal probability of capture throughout the removal process, such that the catchability coefficient q is constant, and (3) each unit of effort is independent (so that no two units have either a positive or negative effect on one another), and additive.

Catch-per-unit-effort (CPUE) at time t, denoted U_t, is the ratio of catch and effort. It is related to biomass B_t by

$$U_t = qB_t \tag{1}$$

where q is the catchability coefficient which is the proportion of the population caught with one unit of effort (Quinn and Deriso 1999, p.16). Defining E_t as the cumulative effort up to time t, by substituting the survival equation $B_t = B_0 e^{-qE_t}$ and taking the natural logarithm, we get

(2) $$\ln U_t = \ln(qB_0) - qE_t$$

If present, natural mortality is easily included as

(3) $$\ln U_t = \ln(qB_0) - qE_t - Mt$$ (Chapman 1961; Seber 1982).

Parameter estimates are obtained from a multiple linear regression of ln U versus E and Mt. The negative of the slope provides the estimate of catchability $\hat{q}$, and the estimate of B_0 is obtained by exponentiating the y-intercept and dividing by $\hat{q}$.

In our application, the DeLury estimator is applied to several areas indexed by i. The generalization of (3) is then

(4) $$\ln U_{i,t} = \ln\lfloor q_i B_{i,0} \rfloor - q_i E_{i,t} - M_i t\ .$$

If the average catchability is q, then local depletion occurs when a positive q_i greater than q results in a more negative slope. Significant local depletion occurs when the difference is statistically greater than 0 which implies that catching pollock becomes increasingly difficult. Equation (4) allows natural mortality to be estimated as the regression coefficient related to the independent variable t. However, to avoid confounding between q, B_0, and M, we set $M = 0.3$, the value used by Ianelli et al. (2003).

3.2.2 Description of the data

The data for this work comes from the National Marine Fisheries Service observer program. We compiled all records of pollock catch from the years 1995-1999, of which the most important types of information are records of fishing location to the nearest minute in latitude and longitude, the pollock catch weight in kilograms, and haul time in minutes, all on the scale of an individual haul. We determined that primarily, only hauls containing 50% pollock or more by weight targeted pollock, hence only these hauls were utilized (Battaile and Quinn, 2004). The CPUE data from the observer program was then standardized to reduce variability in the CPUE data unrelated to the population size and catchability, using a general linear model (GLM) (Battaile and Quinn, 2004). Total daily effort was estimated by dividing the total pollock catch (including bycatch) by the average standardized CPUE for that season/area. Cumulative effort was then tabulated from the daily effort values. The residuals (observed-predicted) in lnCPUE from the GLM were scaled upward by adding the median fitted value of the standardization. This scaling made sighting errors easy and a reasonable estimate of initial biomass possible, but does not affect the slope magnitude.

3.2.3 Depletion analysis

The spatiotemporal scale for the analysis was determined from characteristics of the fishery and the biology of pollock. The temporal stratification has two levels, year and season (see Appendix A.1 for details on the season structure). The spatial stratification was performed using Alaska Department of Fish & Game (ADF&G) reporting areas, which are approximately 30 by 34.5 nautical mile blocks. There were many ADF&G areas in the Bering Sea with too little data to perform depletion analysis. We first examined the top 20 area/season strata with the highest pollock haul weights. We also examined important sea lion areas, as shown by the area outlined in bold in Figure 1 representing the Critical Habitat Catcher Vessel Operation Area (CHCVOA) and surrounding areas, which included many of the areas with the highest pollock catches. We then examined between 11 and 21 more strata (depending upon the year). These strata were also chosen depending on the greatest total pollock catches that were not in the first two examinations. The lowest total pollock catch in this last group ranged between 2 and 3.5 million kilograms. For the years 1995-1998, between 73 and 82 ADF&G area/seasons for each year were examined for analysis (Table 1). Data in 1999 were treated in the same manner, however, because the seasons were further stratified into four (A1, A2, B and C) instead of two seasons (A and B), 142 area/seasons were examined. Generally, just less than half of the areas were ultimately not analyzed due to inadequate data quality, meaning not enough total hauls (less than 30) or large temporal gaps in the data (generally more than a week). Individual hauls were removed from a data series if the CPUE was so low as to not indicate targeted fishing; for example, catching less than 1,000 kilograms while trawling for over 3 hours. Finally, days with a single haul, if they were the first or last day in a data set and were uncharacteristically low, were removed.

Linear regressions of the DeLury model were performed on the selected areas. The statistical significance of the regression was tabulated for all areas. If depletion is not occurring, then the overall number of positive and negative q coefficients should follow a 50/50 ratio, with 5% of these being significant based on chance alone with a two-sided α of 0.05. These ratios were tested with standard χ^2 tests.

3.2.4 Comparison with stock assessment results

The annual stock assessment for the entire eastern Bering Sea population of walleye pollock produces rigorous estimates of fishing mortality by age and year. We further interpolated daily estimates of fishing mortality rate and corresponding seasonal catchability estimates for the entire population based on daily catch and effort values (Appendix B). These catchability estimates represent average values for the population as a whole each year. The slopes by area from depletion analysis were then compared against the annual average to determine if the magnitude of depletion from depletion analysis was similar to that from the stock assessment.

3.2.5 Post hoc Analysis

Depletion variables were examined in relationship to characteristics of the fishery and the Bering Sea pollock population. To determine which spatial, temporal and fishery characteristics may be related to the magnitude of depletion we performed a number of analyses using the general linear model (Quinn and Deriso 1999, p. 18-19). We examined 2 different dependent variables, the slope of the depletion estimate and estimated cumulative depletion calculated as $(CPUE_0 - CPUE_t)/CPUE_0$, where a smaller fraction indicates greater cumulative depletion. While related, these two variables describe different fishing effects; the slope indicates the speed at which depletion is occurring while the cumulative depletion indicates the overall final impact of the fishing. The explanatory variables include temporal and spatial relationships, as well as variables related to sea lions. These include year, season, area, survey biomass of the bottom 3 meters (see Appendix A.3 for explanation on assignment of biomass estimates to ADF&G areas), distance of the ADF&G area centroid to Dutch Harbor, if the ADF&G area was in the CHCVOA (the area outlined in bold in Figure 1) or not, if the centroid of the ADF&G area was in the Bering Sea Pollock Restriction Area (BSPRA) of the western CHCVOA (shaded area in Figure 1just north of the archipelago (Department of Commerce, 2003)), total catch, total effort and the ratio of the bottom survey biomass/total catch, the distance from 5 Steller sea lion protected areas in the CHCVOA on the islands Unalaska, Akutan, Akun, Unimak, and Amak islands and finally, the distance from the archipelago in terms of the number of ADF&G areas. We used two season factors because the 1999 fishery was broken into 4 seasons, in one factor we include the A1, A2, B and C seasons from 1999 as separate levels, in the other, the A1 and A2 seasons are collapsed into the A season and the C season is collapsed into the B season. An additional acoustic survey was available for 1996, 1997, and 1999 which was added on to the bottom biomass for a final variable and only data for those three years was used when analyzing that variable. Three DeLury results had unique seasons associated with them and were removed when analyzing the season factors. Three DeLury estimators did not have associated survey biomass estimates and were not included in the analysis with that variable. Finally, no bottom survey data could be associated with 38 of the DeLury results, and no acoustic survey data could be associated with 18 of the DeLury results, so when those variables are analyzed the appropriate data are excluded.

We analyzed main effects individually because models of even moderate size could contain factor combinations without data . We stratified the data in a number of ways for analysis to examine possible differences by area (within and around the CHCVOA (ADF&G areas depicted in Figure 1), or the whole of the Bering Sea), year (before and after the management changes of 1999), and different slope signs and significance estimates of the DeLury models. Table 2 indicates each stratification structure used, for a total of 20, and the independent variables examined.

Schooling behavior of pollock is related to ambient light (Taina Honkalehto pers. com., NMFS, Seattle, Wahington) so whether a haul was made during daylight or night was calculated. An algorithm was obtained from the Internet as a spreadsheet with a user-defined macro by Pelletier (2003) that calculated sunrise and sunset times given latitude, longitude and day of the year. Hauls were classified as occurring in the night or day depending on whether the timing of the middle of the haul occurred between sunset and sunrise or between sunrise and sunset respectively.

The log of estimated initial biomass was plotted against bottom trawl estimates of pollock biomass for each ADF&G area to determine if the model estimates and field estimates were proportional and agreed with each other.

The DeLury analysis was performed using an Excel spreadsheet and its native regression analysis. Mapping of the results was performed using GIS software. Analysis of DeLury results was performed using S-plus and Excel add-ins.

3.3 RESULTS

3.3.1 DeLury depletion results

Figure 2 illustrates a typical DeLury depletion estimator regression plot and a scatter plot of the untransformed CPUE data. The slope is close to 0 with a low R^2 but is significantly negative. The untransformed data shows a much more pronounced decrease in CPUE near the end of the season than does the transformed data.

Many areas show significant depletion across years and seasons, while other areas show more sporadic occurrences (Figure 3). Generally, the pattern of depletion moves away from the CHCVOA during the B season. Figures 4 and 5 illustrate some interesting with-season results of seasons 1997B and 1999A1, respectively. In 1997B, a large number of areas far away from the CHCVOA had significant depletion, while 1999A1 shows particular reduction in depletion in all areas.

172 of the 237 slopes from the DeLury analysis were negative with over 55% (94) significant at the $\alpha<0.05$ level (Table 3). The fraction of significant positive slopes is fewer with 19 of 65 significant at the $\alpha<0.05$ level. The greatest percentage of positive and significantly positive slopes occurred in 1999, the first year Steller sea lion measures went into affect.

More slopes were significantly negative each year than the expected 5% positive slopes. Pooling over the years does result in both significantly more negative and positive slopes.

3.3.2 Comparison with stock assessment results

Estimates of q (seasonal) from the 2001 stock assessment (Ianelli et al. 2001) tend to be between 0.00001 and 0.00002 indicating that the catchability coefficient of the fishery is fairly constant over the five years (Table 4). No differences were found between seasons ($n=5$, $t=1.68$, $p=0.17$). From the depletion analysis, the comparable slopes of the linear regressions (Figure 6) were smaller in absolute magnitude than the stock assessment q values which average 1.58E-05, with many one to two orders of magnitude smaller.

3.3.3 Post hoc analyses

For the CHCVOA dataset, the dependent variables for depletion slope and cumulative depletion were correlated with measures of distance within the CHCVOA and surrounding area (Table 5). All but one of the 27 significant results indicates that cumulative depletion and the magnitude of the slope decreases as distance from the islands increase, meaning that depletion is greatest nearest the islands and Steller sea lion rookeries and haulouts. The year, season, and area variables were rarely correlated with the dependent variables. The dependent variables were significantly correlated with total catch and effort, only 25% of the time. Yet slopes became more positive and cumulative depletion decreased as effort and catch increased. The strongest and most consistent relationship was with the natural log of initial biomass indicating that slope magnitudes became more negative and cumulative depletion increased as estimated initial biomass decreased.

With all data, certain areas were quite different and the A seasons, particularly A1 in 1999, generally showed less cumulative depletion and less negative slopes (Table 6). Similar regression results, relative to the CHCVOA data set, with total catch and effort and initial biomass, were found with the total data set but with perhaps even stronger inclinations.

The length of the pollock fishery and the percentage of the quota caught in the CHCVOA for 1995-1999 indicate that the changes that took place in the fishery in 1999 resulted in a much longer season for catcher/processor vessels and much of the catch was dispersed out of the CHCVOA (Table 7). However, the percentage of strata with significant depletion relative to all strata investigated is not much smaller in 1999, 35%, relative to the pooled data of 1995-1998 at 41% (Table 3).

In 1999, seasons A1, A2, B and C had 39, 49, 62 and 52% respectively of the standardized hauls made during the day. In 1998, the A and B seasons had 46 and 50% respectively.

3.4 DISCUSSION

There is a detectable within-season decrease in logarithmic CPUE from the commercial fishery for walleye pollock in many areas in the eastern Bering Sea. This decline is invariably due to some depletion of the population by the commercial fishery and perhaps some emigration from each area. Given the complex suite of processes, including natural and anthropogenic mechanisms, interacting to affect the pollock population dynamics, it is perhaps surprising that such a general trend is observed.

Figure 3 shows two important general trends: the CHCVOA held the overall greatest concentrations of DeLury estimates that indicated significant depletion, which is a Steller sea lion protection zone, and the areas south and west of St. Matthew Island are heavily exploited only in the B season. In general the spatial shift in exploitation takes pressure off of the CHCVOA. In 1997, the highest concentration of depletion estimators in season B occurs near St. Matthew Island, because few estimators in the CHCVOA had enough data to model. Consequently, only two areas in the CHCVOA were found to be depleted.

In 1999 the concentration of effort again shifted away from the CHCVOA (via management interjection). The data of Table 7 clearly shows that the seasons were longer and catch was displaced from the CHCVOA to the south and west of ST. Matthew island.. During the A1 season specifically there is no evidence for depletion in either area. However, the relative percentage of depleted strata was only 5% smaller for 1999 relative to other years indicating that while depletion can be limited by distributing effort, it may be that depletion is only displaced to other areas and times. This may be particularly true if effort is redistributed to areas of lower density where depletion is more easily detectable (explained below). In the end, if depletion is unavoidable, it may at least be containable to times and areas not deemed of critical importance.

Differences of our estimates of q from the DeLury models and the seasonal estimates based on the stock assessments are best explained by the hyperstability of pollock CPUE data. The stock assessment based estimates of q occur within a model that does not incorporate hyperstability of CPUE, hence, q is estimated under the assumption that CPUE changes linearly with abundance, resulting in a catchability coefficient greater than that indicated by the CPUE data.

Comparison of DeLury slopes with stock assessment results shows that it is likely that the actual level of depletion is underestimated from DeLury analysis of the commercial fishing data. In addition the post hoc regressions of cumulative depletion and catchability with effort, catch and initial biomass all indicate the CPUE-abundance relationship is hyperstable. Due to hyperstability in the relationship between commercial CPUE and pollock abundance, CPUE would remain high despite actual reductions in stock size (Figure 7). Catch data of a schooling fish, given the fish finding capability of today's modern fleet, would show hyperstability over time in its CPUE (Harley et al. 2001). In fact, Quinn and Collie (1990) estimated the CPUE-abundance relationship to be related by the square root of abundance, which results in a hyperstable relationship.

One remedy would be to include search time in the measure of fishing effort, but this variable is not currently recorded. The problem of hyperstability is exacerbated when search time is not included as part of the effort because nets are set on relatively large concentrations of fish. Without an accurate estimate of the CPUE-density relationship and no measure of search time, any finding of depletion would err on the side of finding less depletion.

The effect of hyperstability on these results begs the question of what the biological mechanisms are that result in a scale of spatial variability that would lead to hyperstability at our reporting area level. Because our blocks (ADF&G reporting areas) are essentially randomly sized relative to the biology of pollock, it is assuredly independent of the block sizes. The reasoning of why hyperstability affects the results at the block scale is a combination of why hyperstability occurs within the pollock fishery at all, the assumption of constant catchability and the size of the EBS pollock fishery. The scale is probably much larger than the block sizes because the EBS pollock fishery covers a large area and is prosecuted on an unusually large biomass. The fish finding technology allows fishers to choose where to fish to maximize efficiency and pollock school densities are likely very similar. Because the exploitable biomass is so large and over such a large area, the distances between areas of high catchability are likely small so there is little reason to fish in areas of low efficiency. Hence, the catchability will likely be the same within a reporting area and the effect of hyperstability will be uniform over the sampling block.

The correlations between the DeLury depletion variables and spatial, temporal and fishery characteristics are biologically meaningful. As estimated initial biomass increased, the magnitude of depletion decreased and the slope became less negative. The relationship between slope and cumulative depletion with catch and effort was always positive indicating that areas with greater biomass, and hence effort and catch, showed less inclination for depletion. The results suggest that areas with less fish are more susceptible to depletion, even with proportionally smaller amounts of effort and total catch. A hyperstability curve predicts that depletion is more easily detectable in areas of lower abundance because the slope gets steeper as abundance decreases.

The spatiotemporal scale at which measurements are taken and pooled must be appropriate to the questions at hand. The eastern Bering Sea pollock stock assessment is done at a time scale such that removals are sustainable on a year-to-year basis in a relatively large area. While the quota may be sustainable over the course of a year, the possibility of severe localized depletion cannot be eliminated or easily measured. Spreading out the catch over time and space reduces the magnitude of local depletion; however fishing inherently reduces a fish population prior to growth and recruitment. The scale most appropriate with respect to pollock and Steller sea lions is largely unknown (Barbeaux and Dorn 2003), and sea lion data, with respect to spatial foraging requirements, are limited (Loughlin et al. 2003). Hence, the only alternative is to use the temporal (seasons) and spatial scales (ADF&G reporting areas) at which management is occurring. While this may mean a loss of biologically important information, we are able to evaluate the effects of management decisions at the scale and distribution in which they occur, such as the CHCVOA which follows the perimeter of the ADF&G blocks (Figure 1).

Our choice of which areas to examine was based on the desire to examine the majority of the total eastern Bering Sea pollock catch, and to examine a continuous area within the eastern Bering Sea of importance to the Steller sea lions and pollock fishery. Our post hoc testing does not then strictly follow the assumption of a random sample, as such it would be improper to extrapolate our results to the entire area covered by the pollock fleet. It may however, be appropriate to look upon our samples as primarily a census of the defined areas, in which case the results of the tests are more palatable for drawing general conclusions within those areas. This is adequate for our purposes because we are, using 1995 as an example, analyzing data associated with over 90% of the catch and can draw conclusions about the majority of the pollock fishery.

Much of the catch data is not temporally continuous, with breaks within seasons lasting sometimes for weeks though generally just a few days. Clearly when fishing is not occurring, recruitment and perhaps immigration will replenish the stock, so it was important to use blocks of continuous effort to model. Exploratory data analysis indicated that breaks longer than 7 days began to show evidence of stock replenishment, so we used this length of time as a cut off rule. Figure 8 describes a prime example, fishing was consistent from August 1 to the 18 with approximately 79,500 units of effort expended resulting in significantly negative depletion. From August 19 to September 1st, only 735 additional units of effort were expended for those 12 days, none of which specifically targeted pollock. Starting on the 1st of September light fishing resumed showing a much higher CPUE at levels similar to those found on the first of August, hence in less than two weeks it appears that the population recovered from relatively heavy exploitation. Combined, the two sections result in a DeLury estimator with a significantly positive slope, individually, they show significant depletion on both sides of the break. No other stratum showed such an obvious pattern, due to the fact that it is rare for a significant break to occur between two times of relatively heavy exploitation. While this event is suggestive, a dedicated investigation into the recruitment and recuperation of pollock populations is necessary to make a definitive conclusion.

The greatest problem in detecting depletion is that a large enough proportion of the population is removed so that the depletion signal is detectable. Approximately 10%

of the population biomass is removed each year from the Bering Sea (Ianelli et al., 2003) although this may be concentrated in some areas so that a greater percentage of a local population is taken. Indeed Fritz (1998) estimated between 55 and 91% removal on a local scale in an Atka mackerel depletion study in the Aleutian Islands and Gulf of Alaska even though only 10% of the entire population was scheduled to be harvested based on stock assessments for the examined years. With these harvest rates, Fritz found significant depletion in 8 of 9 Leslie depletion estimates. The estimated percentage of the pollock population removed from our strata that indicated significant depletion, ranged from only a 2% to 30% reduction of the original biomass. Most certainly the lower level of pollock removal indicates less severe depletion and is associated with finding a smaller percentage (41%) of the strata to have significant depletion, relative to Fritz (1998).

Walleye pollock exhibit diel differences in schooling behavior with well identifiable schooling during daylight and dispersion throughout the water column at night. The diel differences in schooling behavior should create significant differences in catchability over a 24 hour period and at extreme latitudes, the relative amount of time spent dispersed will vary significantly over the year. Hence, the effect of schooling behavior on estimates will be exacerbated in the summer, so we might expect to see more depletion in the winter months relative to the summer months. For 1999, A1 is closest to the winter solstice and B is closest to the summer solstice creating about a 20% difference between the number of hauls taken during the day or night. In contrast, very little difference occurs between the A and B seasons in 1998. The A season is however the roe season where boats target spawning aggregations, to the extent that they can

(Ianelli et al. 2003), which may counter any differences from the schooling behavior, and incidentally, potential catchability differences between spawning and non-spawning fish. 33% of the A season estimators indicated significant depletion while 44% of the B season estimators did, ratios that are not significantly different at our sample size (n=237, χ^2=1.096, p=0.30). The effect of targeting the spawning aggregations would be very hard to predict and dependent upon the intensity of the immigration and emigration involved in spatial and temporal terms and the numbers of pollock involved as well as the intensity of the exploitation.

With respect to the Steller sea lion problem, our research indicates both positive and negative aspects relevant to the fishing industry. The results of the analysis indicate that biologically significant depletion is occurring in some areas at some times. Given the problems of the DeLury estimator assumptions, the lack of a measure of effort and hyperstability in the CPUE, it is perhaps most surprising that a statistically significant depletion signal is detectable at all. The results here should be considered conservative, erring on the side of finding less depletion. Despite this problem, our results do suggest that depletion can be reduced via diffusion of effort in space and time as was done to some degree in 1999, and that pollock may be able to bounce back from local depletion relatively quickly. While 1999 appears to fare better than the previous years, depletion is still evident with the CHCVOA and the fishery could be further dispersed in space and time to address this. Since 1999, 4-5 years of data have been collected and should be analyzed to confirm our 1999 findings and guide future management. Qualifying the effectiveness of the current measures and the linkage between the fishery and Steller sea lion decline is extremely difficult. It remains unknown what percentage of the decline is due to a lack of pollock in the Steller sea lion diet and, given there is a sea lion decline and pollock connection, what fishing mortality will not effect Steller sea lions.

3.4.1 Acknowledgments

This publication is the result of research sponsored by Alaska Sea Grant with funds from the National Oceanic and Atmospheric Administration Offices of Sea Grant, Department of Commerce, under grant no. NA 86RG0050 (project no. R/101-02) and from the University of Alaska with funds appropriated by the state. This manuscripts has benefited greatly from the help of Jim Ianelli.

3.5 REFERENCES

Bakkala, R.G., Vidar G. Wespestad and L. Low. 1987. Historical trends in abundance and current condition of walleye pollock in the eastern Bering sea. Fish. Res. **5**:199-215.

Bailey, K.M., T.J. Quinn II, P. Bentzen and W.S. Grant. 1999. Population structure and dynamics of walleye pollock, *Theragra chalcogramma*. Adv. Mar. Bio. **37**:179-255.

Barbeaux, S.J. and M.W. Dorn. 2003. Spatial and temporal analysis of eastern Bering Sea echo integration-trawl survey and catch data of walleye pollock, *Theragra chalcogramma*, for 2001 and 2002. U.S. Dep. Commer., NOAA-TM-AFSC-136, 34 p.

Battaile, B.C. and Quinn, T.J. 2004. Catch per unit effort standardization of the eastern Bering Sea walleye pollock (*Theragra chalcogramma*) fleet. Fish. Res. 70: 161-177.

Braaten, D. O. 1969. Robustness of the DeLury population estimator. J. Fish. Res. Bd. Can. **26**:339-355.

Chapman, D.G. 1961. Statistical problems in dynamics of exploited fisheries populations. Pro. 4th Berkeley Symp. Math. Stat. Prob. Contr. Biol. Probl. Med. 4: 153-168.

DeLury, D.B. 1947. On the estimation of biological populations. Biometrics. **3**:145-167.

Department of Commerce. 2003. Fisheries of the exclusive economic zone off Alaska; Steller sea lion protection measures for the groundfish fisheries off Alaska. Federal Register. **68**:204-236.

Dorn, W. E. 1998. Fine-scale fishing strategies of factory trawlers in a midwater trawl fishery for Pacific hake (*Merluccius productus*) Can. J. Fish. Aquat. Sci. 55: 180-198.

Dunn, J. R. and A.C. Matarese. 1987. A review of the early life history of northeast Pacific gadoid fishes. Fish. Res. **5**:163-184

Fadeyev, N. S. 1989. Spatial and temporal variability of the eastern Bering Sea walleye pollock size composition in relation to its migrations. Proc. Int. Symp. Bio. Mgmt. Walleye Pollock. 497-508.

Fritz, L. W. 1998. Do trawl fisheries off Alaska create localized depletions of Atka mackerel (*Pleurogrammus nommopterygius*)? Alaska Fisheries Science Center, National Marine Fisheries Service.

Ianelli, J.N., T. Buckley, T. Honkalehto, G. Walters and N. Williamson. 2001. Eastern Bering Sea Walleye pollock stock assessment. *In*: Stock assessment and fishery evaluation report for the groundfish resources of the Bering Sea/Aleutian Islands regions. N. Pac. Fish. Mgmt. Counc., Anchorage, AK section 1:1-89.

Ianelli, J.N., S. Barbeaux, G. Walters and N. Williamson. 2003. Eastern Bering Sea Walleye pollock stock assessment. *In*: Stock assessment and fishery evaluation report for the groundfish resources of the Bering Sea/Aleutian Islands regions. N. Pac. Fish. Mgmt. Counc., Anchorage, AK section 1:39-126.

Harley, J. S., R. A. Meyers and A. Dunn. 2001. Is catch-per-unit-effort proportional to abundance? Can. J. Fish. Aquat. Sci. **58**:1760-1772.

Leslie, P.H. and D.H.S. Davis. 1939. An attempt to determine the absolute number of rats on a given area. J. Anim. Ecol. **8**:94-113

Loughlin, T.R., J.T. Sterling, R.L. Merrick, J.L. Sease and A.E. York. 2003. Diving behavior of immature Steller sea lions (*Eumetopias jubatus*). Fish. Bull. **101**:566-582.

National Research Council (NRC). 2003. Decline of the Steller sea lion in Alaskan waters. Untangling food webs and fishing nets. National Academy Press, Washington D.C. 204p.

Pelletier, G.J. 2003. Sunrise, sunset, solar position, and solar radiation calculators for Excel. http://users.vei.net/pelican/sunrise.html

Polovina, J. J. 1986. A variable catchability version of the Leslie model with application to an intensive fishing experiment on a multispecies stock. Fish. Bull. **84**:423-428.

Quinn, T. J. II. 1987. Standardization of catch-per-unit-effort for short-term trends in catchability. Nat. Res. Mod. **1**:279-296.

Quinn, T.J., II, and J.S. Collie. 1990. Alternative population models for eastern Bering Sea pollock. Int. N. Pac. Fish. Comm. Bull. **50**: 243-257.

Quinn, T.J. II, Deriso, R.B., 1999. Quantitative Fish Dynamics. Oxford University Press, New York.

Ricker W.E. 1975. Computation and interpretation of biological statistics of fish populations. Fish. Res. Brd. Can., Bull. No. 191.

Seber, G.A.F. 1982. The estimation of animal abundance, 2nd edition. Griffin, London.

3.6 Appendix A

3.6.A.1 Details of the pollock fishery and seasons

The changes in the seasonal structure beginning in 1999 deserves some elaboration as the Steller sea lion measures were designed to impact the spatial and temporal distribution of the pollock fishery and the effects on the results obtained here are likely to be significant. The season structure from 1995 to 1998 was fairly simple, there was an onshore and offshore sector each broken into and A and B season which roughly took place from late January to late February and from early September to late October respectively, for both sectors. In 1999, the complexity was greatly increased. There are three sectors, inshore, catcher/processors and motherships which are purely processors each with a different seasonal structure. Catcher/processors have an A1 season from late January to mid February, an A2 season from mid February to mid April, a B season from early August to mid September and a C season from mid September to early November. The motherships have a B/C season from early August to late September and the A season is now broken into to sectors defined by the size of boat catching for them and where the catching is occurring. Boats over 99 feet in length are not allowed to fish in the CHCVOA after a certain quota is obtained. The entire A season lasts from the first of February to the 17th of February but the restricted access began on the 10th of February. The inshore sector has an A1 season from Jan. 20 to Feb. 15, an A2 season from Feb. 20 to Feb.28, a B season from Aug. 1 to Aug. 26 and a C season from Sep. 15 to Aug. 6. As before, boats over 99 feet in length are not allowed to fish in the CHCVOA after a certain quota is obtained, generally restricting their access for the last week of each season. Pollock fishing is prohibited outside the shaded areas within the CHCVOA at all times.

3.6.A.2 Consideration of DeLury assumptions

Assumption 1, a closed population, refers to recruitment, immigration, emigration and natural mortality, all of which cause problems in marine fisheries. For our purposes though we can relax this assumption to some degree, and design the analysis to minimize violations. Pollock are a migrating species on many different scales. At the largest scale in the eastern Bering Sea, they tend to migrate from the northwest to the southeast as they mature (Fadeyev 1989). They also congregate seasonally in certain areas to spawn (Bailey et al. 1999) and of course smaller scale movements are inherent. Temporal and spatial scales can be used that minimize known migratory effects. While recruitment into the fishery may inhibit the ability of the DeLury estimator to determine the size of the population at the beginning of the experiment, or what percentage of the original population has been fished, with respect to the practical problems of the Steller sea lion and human fisheries, what we are primarily interested in is if the fishery is causing depletion DESPITE recruitment, because if the population could recruit at the same rate that fishing removes individuals, there would be no problem. For mortality, we could assume a natural stable population, such that mortality equals recruitment, a reasonable assumption over small time periods. A more conservative and satisfying approach would be to estimate mortality and essentially remove its signal from the data, such that the reduction in the population due to mortality is not confused with fishery mortality.

Assumption 2 refers to catchability. All fish must have an equal and constant catchability over the spatiotemporal span of the removals. There are numerous biological and fishing related processes that could violate this assumption. Often, fish of different age and size have different behaviors that lead to different catchabilities due to the fishing methods or gear used. So long as the gear can be standardized and the targeted age or size remains the same, this is unlikely to be a problem. However, the catchability for the target fish can change with season and area, for example, spawning aggregations are targeted by the pollock fleet. So long as these special exceptions can be isolated they should also not be a problem. Fish density would clearly have an impact on the catchability in a couple of different ways. Pollock are known to school in the day time and disperse at night for feeding (Honkalehto, pers. com. 2000), clearly a net hauled through a school will have a greater CPUE than one hauled through a water column with dispersed individuals. Again, if solar times are known, this can be standardized for.

Assumption 3 requires independent and identically distributed data for valid regression analysis. Indeed, we might expect hauls that are close together to be similar, as subsequent hauls may occur on the same school of fish, however we assume that such similarities are not significant as many factors play a part in the decisions considering when and where to fish (Dorn 1998), particularly for boats that both catch and process fish, which are a large percentage of the pollock fleet (Battaile et al., in review).

3.6.A.3 Assignment of survey data to ADF&G reporting areas

The NMFS survey sampling grid and ADF&G reporting areas do not overlap in a convenient manner for comparison, hence some data preparation was required to assign survey samples to appropriate ADF&G areas. The NMFS sampling grid is regular and each sampling point is meant to estimate the pollock biomass in the surrounding 400 square nautical miles. Each point was given a value of 1, 0.5 or 0.25 depending upon the approximate percentage of it's 400 square nautical miles that was contained within a particular ADF&G reporting area. A weighted average, estimating the density of pollock in an ADF&G area was then calculated using the following equation

$$\sum_{i=1}^{n}(d_i * p_i) \Big/ \sum_{i=1}^{n} p_i ,$$

where d is the sample density, p is the percentage of the sample within an ADF&G reporting area and i is the number of samples within a single reporting area. ADF&G areas are typically 900 square nautical miles so the weighted average was multiplied by 2.25 to estimate the total biomass in one reporting area. For those ADF&G areas that are not square due to adjacent islands, the approximated percentage of a full square was estimated and used to adjust the final result.

3.6.A.4 Relationship between bottom trawl survey biomass and estimated biomass

No discernable relationship existed between our estimated initial biomass and the biomass estimated by the trawl survey. There are two likely reasons for this. Our estimate of initial biomass is biased. Given the hyperstable nature of the CPUE/abundance relationship, we will typically underestimate the initial biomass for areas of high biomass and over estimated it for areas of low biomass. The other reason is the trawl surveys may be quite variable and, while provide an adequate estimate over larger spatial ranges such as the eastern Bering sea, it is likely that pollock are highly patchy and individual trawls taken at predefined points on a grid are quite variable. Each bottom trawl represents a 20 by 20 nm square grid which is approximately 2/3's the size of our ADF&G areas so that the bottom trawl estimate for each ADF&G area depends on the results, on average, of 1.5 bottom trawls, a number of replicates to small to accurately estimate the abundance of a patchy prey.

3.7 APPENDIX B

3.7.B.1 Equations for calculation of q

$N_{j,i}$- number of fish, using method j and day k, given a population starting with 10,000 individuals

C_i- total catch from observer data in season i

F- fishing mortality from Ianelli et al. (2001)

M- natural mortality from Ianelli et al. (2001)

Ti- number removed from population due to F or M given a population of 10,000

FT_i- daily average number of fish removed for season i given a population of 10,000

FT_{os}- daily average number of fish removed for off-season given a population of 10,000

L_i- length of season i in days

D- days in a year

S_i- survival rate due to source i (F or M)

E_i- daily effort from targeted (i=T) and non-targeted or no effort data (i=NT) pollock catch

$C_{\%OS}$- percentage of total pollock catch taken in the off-season

q- catchability

3.7.B.2 SAFE Report Population

The first population derives from the fishing mortality rates found in the SAFE reports. The report assumes a constant F yet the fleet has well defined seasons hence, congregating the catch into these limited dates is essential. Given the SAFE F and M, the number of individuals (from 10,000) taken by the fishery and natural mortality is determined. The mortality due to F is then partitioned to the seasons and off-season based on the daily recorded catch from the observer data scaled to the virtual population. The catch partitioned to a season is spread evenly over the entire season in daily increments. Mortality due to M is removed via a daily survival rate based on M=0.3.

Total mortality for a year given a population of 10,000

$$T_{F+M} = 10{,}000(1 - \exp(-(F + M))).$$

Percentage of yearly mortality due to fishing

$$T_F = \frac{F}{F + M} * T_{F+M}.$$

Daily mortality given in numbers of fish for season i from fishery adjusted to population of 10,000

$$FT_i = \frac{C_i}{C} * \frac{T_F}{L_i}.$$

Daily survival rate due only to natural mortality

$$S_M = \exp(-\frac{M}{D}).$$

Number of fish remaining on day k starting with 10,000 due to natural and fishing mortality

$$N_{SAFE,k} = N_{SAFE,k-1} * S_M - FT_i.$$

3.7.B.3 *F=Eq* Population

Here we determine the amount of effort expended in the fishery and calculate F using $E*q$, remove fishery and natural mortality and finally subtract out off-season catch. We have categorized effort in the fishery into three types of hauls. Those hauls that have greater than 50% pollock by weight in the catch (targeted pollock catch), those that have less than 50% pollock (presumed non-targeted), and those that have no effort data associated with the catch. For the hauls with greater than 50% pollock, the effort is summed for a day. For those hauls with no effort data or less than 50% pollock, the haul weight is multiplied by the ratio of (total effort)/(total weight) from the hauls with greater than 50% pollock. This is done for each season separately and effectively standardizes all catch in terms of directed pollock fishery effort units. This new standardized effort is totaled for each day and added on to the targeted pollock effort for E.

E_{NT} is standardized to E_T by

$$E_{NT} = C_{NT} * \frac{E_T}{C_T}.$$

Total effort standardized to targeted effort

$$E = E_T + E_{NT}.$$

Percentage of total catch taken in the offseason

$$C_{\%OS} = \frac{C_{os}}{C}.$$

Daily removals in off-season due to fishing

$$FT_{OS} = C_{\%OS} * \frac{T}{D_{OS}}.$$

To bring the off season catch, M and F=Eq mortality together, a daily survival rate is calculated where M=0.3 and $E*q$ is substituted for F, where q is estimated. This daily survival rate is multiplied by the previous days abundance and then the off-season catch is subtracted if applicable.

Daily survival rate where M=0.03 and F=Eq

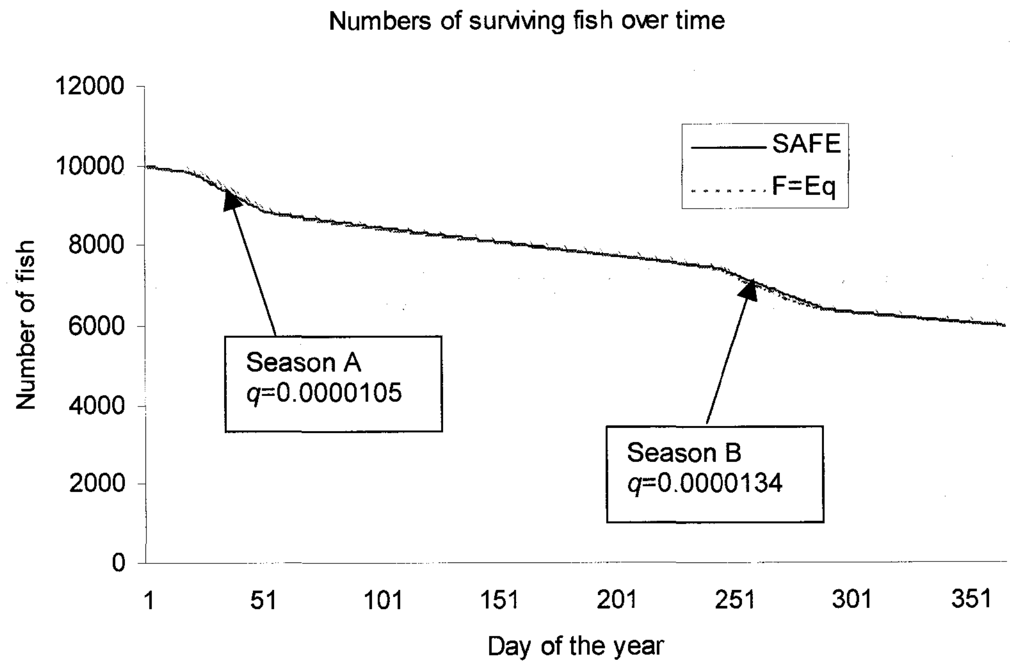
$$S_{F+M} = \exp(-\frac{F+M}{D}).$$

Number at day k such that q is the only unknown

$$N_{F=Eq,k} = N_{F=Eq,k-1} * S_{F+M} - FT_{OS}.$$

With two working separate population models q is subsequently estimated using a non-linear search algorithm minimizing, using least squares, the difference between the daily logarithm of remaining individuals from the "SAFE F" and "F=Eq" populations.

$$\sum_{k=1}^{D} (\ln N_{SAFE,k} - \ln N_{F=Eq,k})^2.$$



Appendix Figure B-1. Surviving fish from simulated populations for estimating q from 1997. The populations trends from the SAFE and F=Eq populations are essentially indistinguishable from one another after MLE.

Table 3.1. The number of ADF&G areas examined for adequate data and the number ultimately analyzed via the depletion estimator.

Year	Number of areas examined	Number of areas analyzed
1995	82	46
1996	80	55
1997	76	40
1998	73	41
1999	142	58

Table 3.2. General linear models performed indicating the dependent variables available in the first column and stratification procedures in top four rows. A "1" indicates a variable was investigated using the data in that column.

Area stratification	Model using CHCVOA and surrounding areas												Model using all areas							
Year stratification	1995-1999				1995-1998				1999				1995-1999							
Independent variables	Cum. Depl.		Slope		Cum.. Depl.		Slope		Cum. Depl.		Slope		Cum. Depl.				Slope			
Dependent variables	All Depletion estimators	Depletion estimators with negative slopes	All Depletion estimators	Depletion estimators with negative slopes	All Depletion estimators	Depletion estimators with negative slopes	All Depletion estimators	Depletion estimators with negative slopes	All Depletion estimators	Depletion estimators with negative slopes	All Depletion estimators	Depletion estimators with negative slopes	All Depletion estimators	All significant estimators positive and	All negative estimators	Significant negative estimators	All Depletion estimators	All significant estimators positive and	All negative estimators	Significant negative estimators
Year	1	1	1	1	1	1	1	1					1	1	1	1	1	1	1	1
Season	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Season AB	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ADF&G Area	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Bottom survey biomass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Total catch	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Total effort	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Bottom survey biomass / Total catch	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ln Initial biomass (B_0)		1		1		1		1		1		1			1	1			1	1
Bottom survey + Acoustic survey biomass													1	1	1	1	1	1	1	1
Distance to Dutch Harbor	1	1	1	1	1	1	1	1	1	1	1	1								
Inside CHCVOA	1	1	1	1	1	1	1	1	1	1	1	1								
Inside BSPRA	1	1	1	1	1	1	1	1	1	1	1	1								
Distance to Unalaska Island	1	1	1	1	1	1	1	1	1	1	1	1								
Distance to Akutan Island	1	1	1	1	1	1	1	1	1	1	1	1								
Distance to Akun Island	1	1	1	1	1	1	1	1	1	1	1	1								
Distance to Unimak Island	1	1	1	1	1	1	1	1	1	1	1	1								
Distance to Amak Island	1	1	1	1	1	1	1	1	1	1	1	1								
Distance in ADF&G Areas	1	1	1	1	1	1	1	1	1	1	1	1								

Table 3.3. χ^2 tests for expected proportions of positive and negative slopes and significant and non significant slopes given the null hypothesis of no depletion.

	1995	1996	1997	1998	1998	Combined
# significant neg	16	21	20	17	20	94
# non significant	26	29	18	21	30	124
# significant pos	3	3	2	4	7	19
Chi2 (Pearson's)	17.9	23.7	24.7	21.6	28.0	114.9
df	2	2	2	2	2	2
P value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
# not significant pos	42	50	38	38	50	218
# significant pos	3	3	2	4	7	19
Chi2 (Pearson's)	0.19	0.11	0	0.8	2.68	6.2
df	1	1	1	1	1	1
P value	0.66	0.74	1	0.371	0.101	0.013

Table 3.4. Estimated values for the catchability coefficient q by season, 1995-1999 from the stock assessment, using methods outlined in Appendix B.

Season	1995	1996	1997	1998	1999
A(1)	1.79E-05	1.24E-05	1.05E-05	2.28E-05	1.20E-05
A2					1.21E-05
B	1.17E-05	1.08E-05	1.34E-05	9.97E-06	7.83E-06
C					4.79E-05

Table 3.5a, b and c. Significance values of linear models using CHCVOA, and surrounding areas, depletion estimators only. Table a uses data from 1995-1999, table b uses data from 1995-1998, and table c uses data from 1999. Values in parenthesis indicate the sign of the associated coefficient. Dummy variables (0,1) were used to indicate whether an area was inside or outside the BSPRA or CHCVOA for those two independent variables, in which case a 1 indicates an area was inside.

Dependent Variable	Cumulative Depletion		Slope	
DeLury slope type	All	Negative	All	Negative
Year	0.62	0.47	0.71	0.11
Season	0.016 (A1+)	0.07	0.09	0.09
SeasonAB	0.06	0.11	0.79	0.2
ADF&G area	0.098	0.47	0.3	0.15
Survey bottom biomass	0.66	0.44	0.91	0.98
Total catch	0.42	0.54	0.52	0.003 (+)
Total effort	0.06	0.66	0.55	0.003 (+)
Survey biomass/catch	0.23	0.63	0.82	0.2
ln Initial biomass	na	<0.001(+)	na	<0.001(+)
Distance to Dutch Harbor	<0.001(+)	0.007 (+)	0.54	0.65
Inside BSPRA	0.6	0.9	0.22	0.3
Inside CHCVOA	0.068	0.016 (1 is -)	0.64	0.8
Unalaska Island	.001 (+)	0.007(+)	0.36	0.76
Akutan Island	.002 (+)	0.005(+)	0.68	0.62
Akun Island	0.84	0.67	0.98	0.99
Unimak Island	0.023 (+)	0.008(+)	0.76	0.64
Amak Island	0.33	0.43	0.19	0.96
Distance in ADF&G areas	0.24	0.05	0.36	0.45

Dependent Variable	Cumulative Depletion		Slope	
DeLury slope type	All	Negative	All	Negative
Year	0.32	0.62	0.39	0.23
Season	0.58	0.4	0.22	0.08
SeasonAB	na	na	na	na
ADF&G area	0.06	0.48	0.14	0.1
Survey bottom biomass	0.67	0.32	0.78	0.98
Total catch	0.39	0.77	0.39	0.014(+)
Total effort	0.07	0.53	0.37	0.010(+)
Survey biomass/catch	0.17	0.41	0.75	0.28
ln Initial biomass	na	<0.001(+)	na	<0.001(+)
Distance to Dutch Harbor	0.002 (+)	0.017(+)	0.35	0.54
Inside BSPRA	0.19	0.57	.041 (1 is -)	0.45
Inside CHCVOA	0.035 (1 is-)	0.06	0.21	0.82
Unalaska Island	0.002 (+)	.016(+)	0.26	0.63
Akutan Island	0.002 (+)	.016(+)	0.42	0.51
Akun Island	0.97	0.55	0.84	0.82
Unimak Island	0.016(+)	.046 (+)	0.72	0.47
Amak Island	0.4	0.99	0.29	0.88
Distance in ADF&G areas	0.29	0.24	0.48	0.22

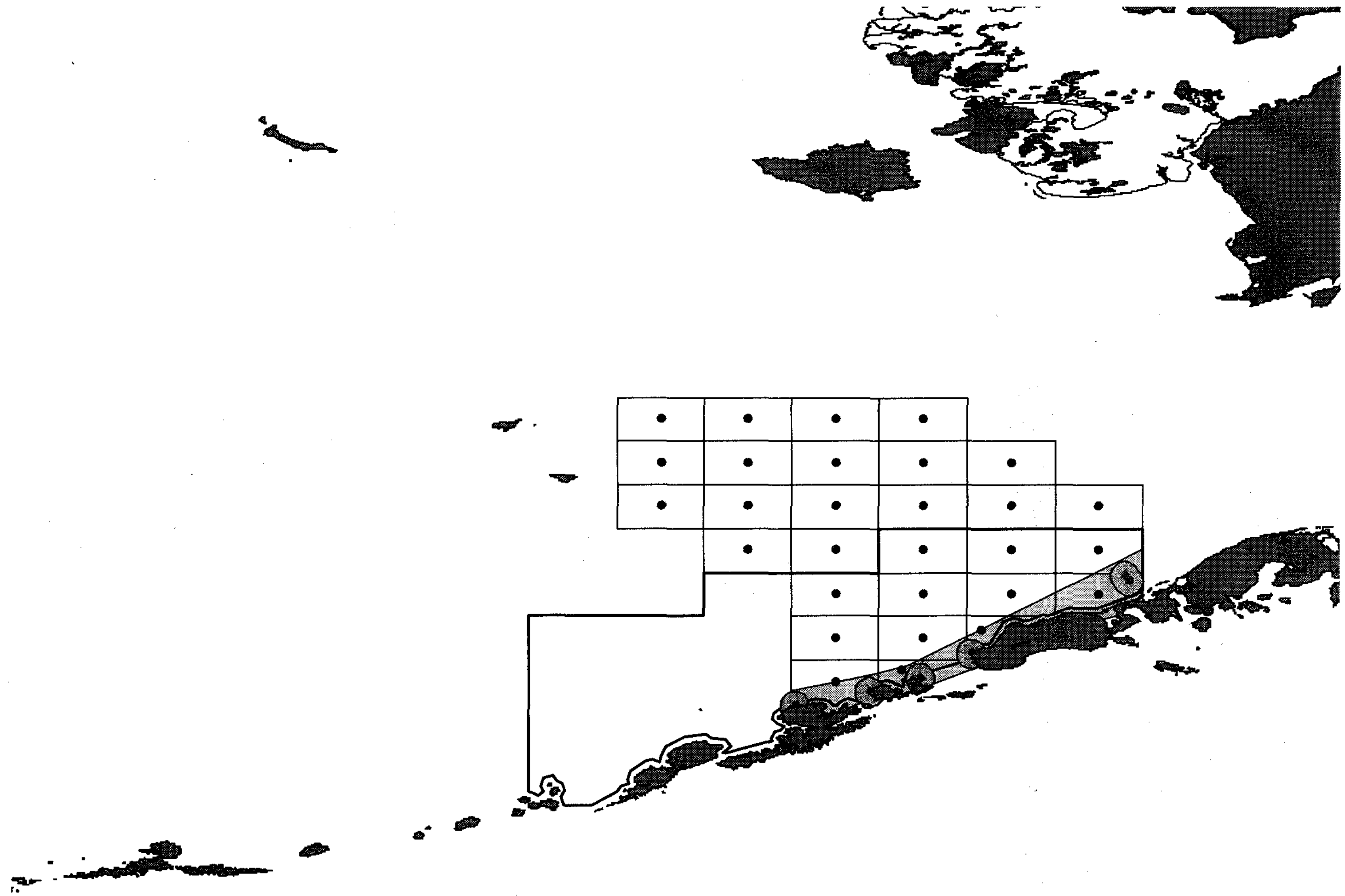
Dependent Variable	Cumulative Depletion		Slope	
DeLury slope type	All	Negative	All	Negative
Year	na	na	na	na
Season	0.06	0.31	0.29	0.64
SeasonAB	0.027 (B-)	0.17	0.11	0.79
ADF&G area	0.17	0.7	0.001	0.59
Survey bottom biomass	0.55	0.031 (-)	.021 (+)	0.015 (-)
Total catch	0.86	0.79	0.98	0.09
Total effort	0.07	0.13	0.71	0.12
Survey biomass/catch	0.86	0.88	0.94	0.6
ln Initial biomass	na	<0.001(+)	na	<0.001(+)
Distance to Dutch Harbor	0.15	0.018(+)	0.79	0.31
Inside BSPRA	.049 (1 is -)	na	<.001 (1 is +)	na
Inside CHCVOA	0.74	0.036 (1 is -)	0.5	0.41
Unalaska Island	0.11	0.024 (+)	0.99	0.3
Akutan Island	0.21	0.017 (+)	0.95	0.33
Akun Island	0.63	0.71	0.79	0.82
Unimak Island	0.51	0.020(+)	0.38	0.34
Amak Island	0.59	0.14	0.43	0.38
Distance in ADF&G areas	0.59	0.01 (+)	0.46	0.13

Table 3.6. Significance values of linear models using all 237 depletion estimators. Table indicates whether a factor was significant as a main effect and the sign of the coefficient when applicable.

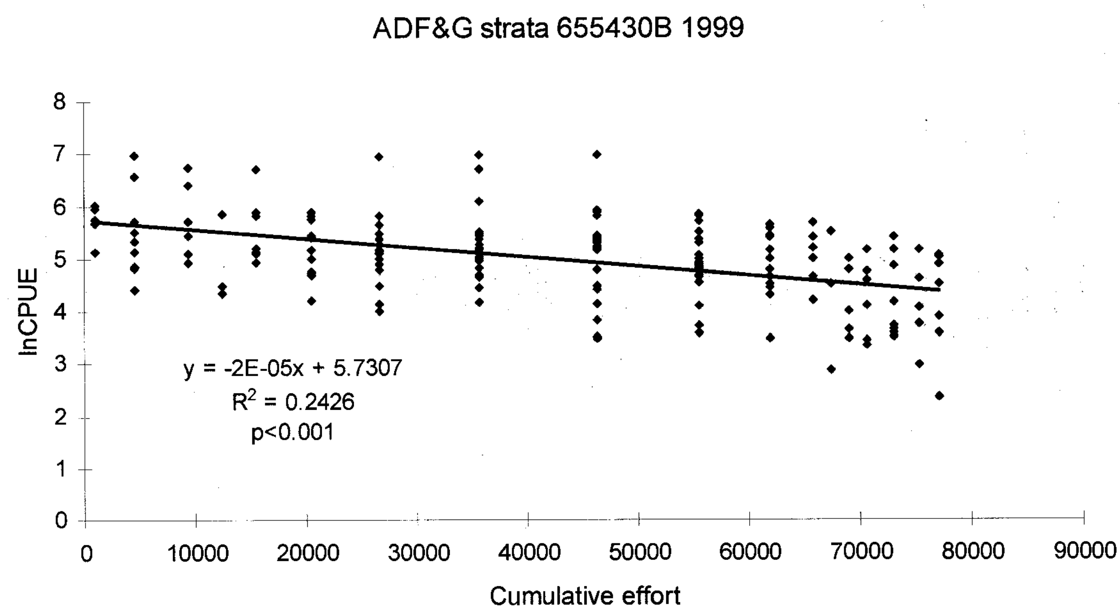
	All Data		All Significant data		Negative data		Significant neg. data	
	Cuml depl	Slope	Cuml depl	Slope	Cuml depl	Slope	Cuml depl	Slope
year	0.89	0.67	0.87	0.87	0.33	0.71	0.18	0.51
season	.002 (A1A2+)	0.41	<0.001 (A1+)	0.23	.033(AA1+)	0.94	0.21	0.92
seasonAB	.004(A+)	0.16	.002 (A+)	0.14	.006(A+)	0.36	0.057	0.51
area	0.1	<0.001	0.03	<0.001	0.028	<0.001	0.45	<0.001
bottom	0.73	0.75	0.28	0.32	0.44	0.75	0.26	0.54
bottom + acc	0.56	0.69	0.76	0.78	0.67	0.54	0.72	0.38
effort	0.09	0.25	0.91	0.21	0.99	0.037 (+)	0.02 (+)	0.046 (+)
catch	0.6	0.2	0.34	0.18	0.27	0.03 (+)	<0.001 (+)	0.038 (+)
lnB_0	na	na	na	na	<0.001 (+)	<0.001 (+)	<0.001 (+)	<0.001 (+)

Table 3.7. Length of season in days broken down by sector and the percentage of catch taken in the CHCVOA based on the available data for the depletion estimators after standardization and removal of the 50% pollock cut off data. CP is catcher/processor and MS is mothership.

Inshore	1995	1996	1997	1998	Average	1999	
A (A1 + A2)	40	42	30	37	37.25	36	
B (C)	39	47	45	58	47.25	50.75	
Offshore						CP	MS
A (A1 + A2)	26	31	25	25	26.75	51	17
B (C)	36	47	31.5	49	40.875	93	58
% CHCVOA	59%	47%	51%	49%	52%	32%	



Figures 3.1. Map of the Bering sea and Aleutian islands showing the CHCVOA, outlined in bold, the BSPRA in light shading and Critical habitat areas (hatched circles) surrounding Steller Sea lion haulouts and rookeries within the BSPRA. ADF&G reporting areas (blocks with center points) shown are the focus of much of the papers analysis.



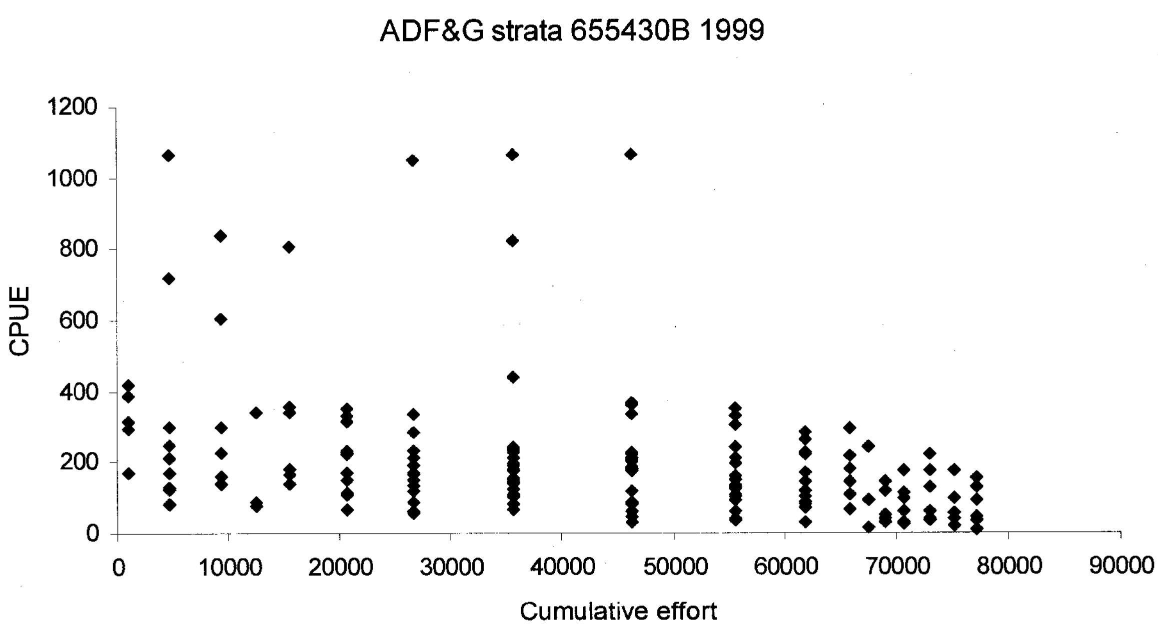
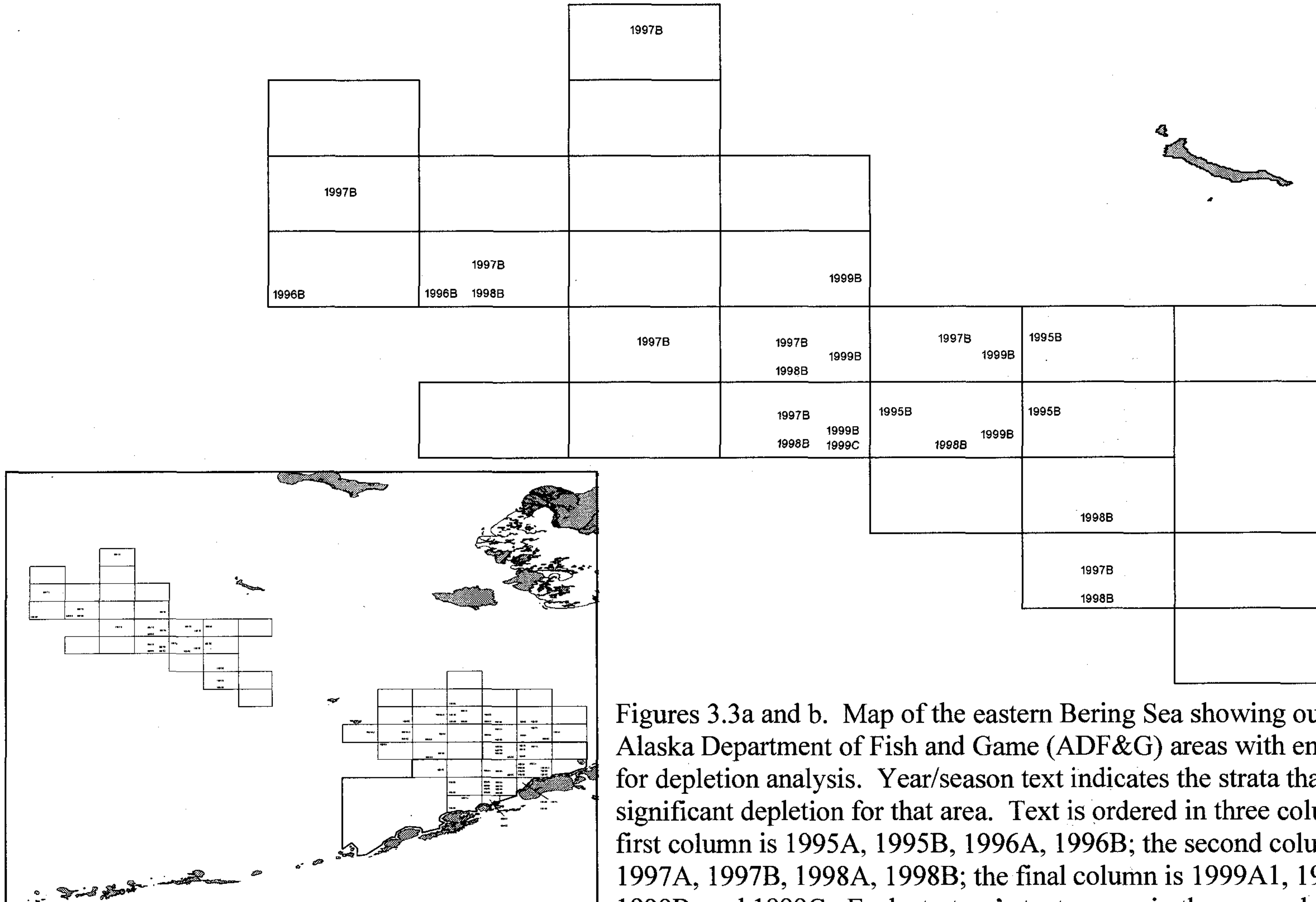
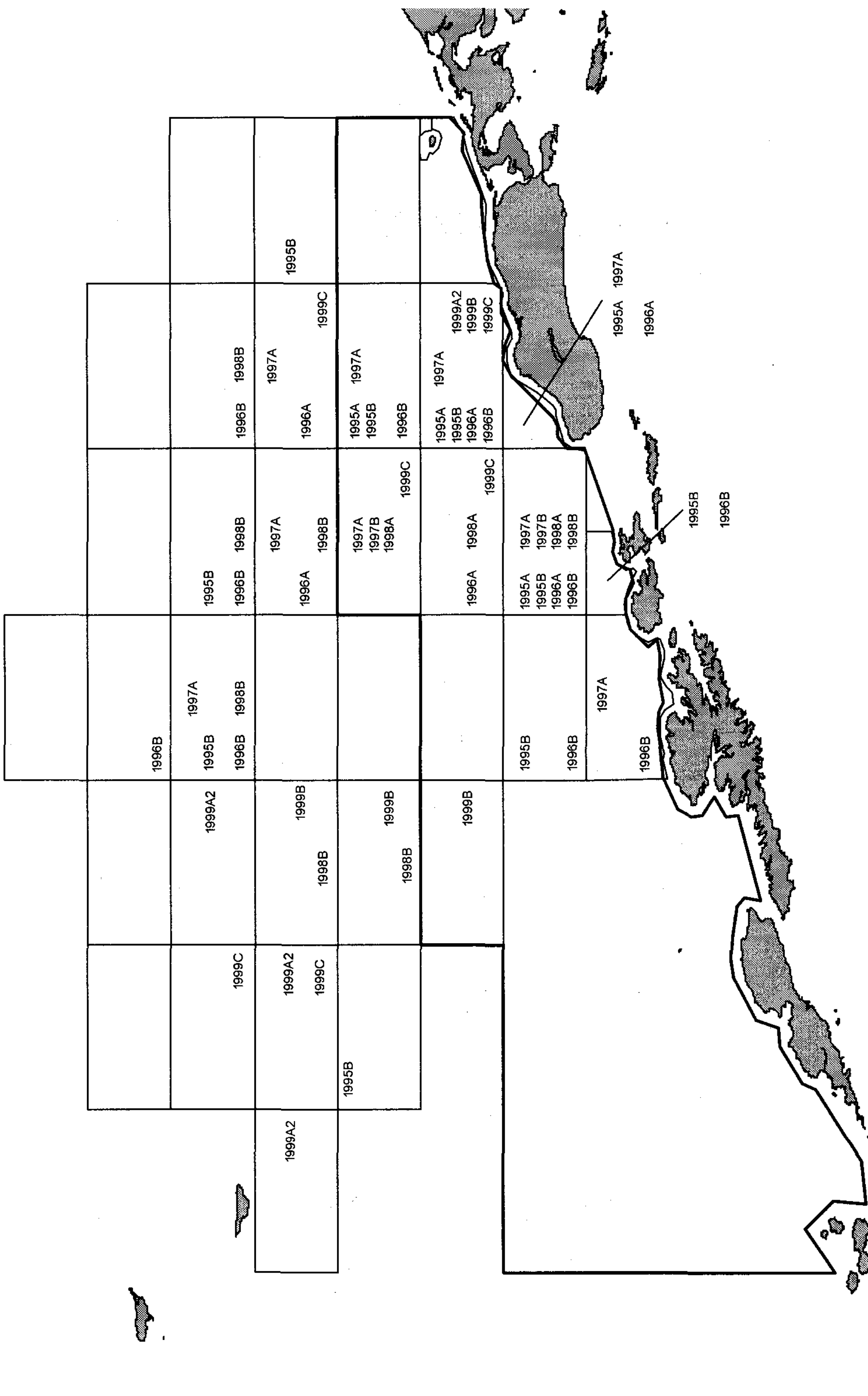


Figure 3.2. Example of a DeLury depletion estimator using the natural log transformation of CPUE and the untransformed CPUE (bottom). From ADF&G area 755830, season C in 1999.



Figures 3.3a and b. Map of the eastern Bering Sea showing outlined Alaska Department of Fish and Game (ADF&G) areas with enough data for depletion analysis. Year/season text indicates the strata that showed significant depletion for that area. Text is ordered in three columns, the first column is 1995A, 1995B, 1996A, 1996B; the second column is 1997A, 1997B, 1998A, 1998B; the final column is 1999A1, 1999A2, 1999B, and 1999C. Each stratum's text occurs in the same place within individual ADF&G reporting areas.



Figures 3.3b. Continuation of figure 3.3.

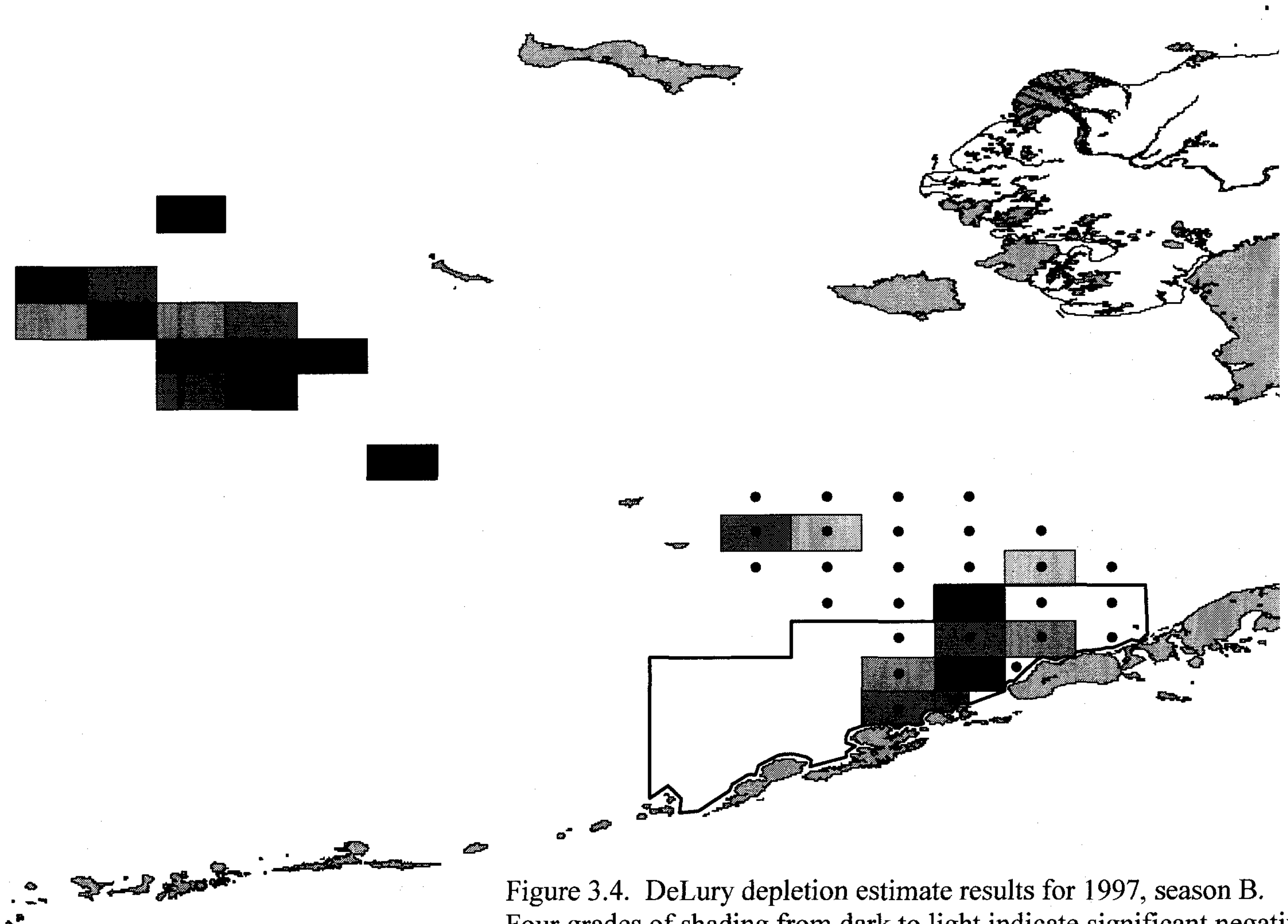


Figure 3.4. DeLury depletion estimate results for 1997, season B. Four grades of shading from dark to light indicate significant negative slope (significant depletion), non-significant negative slope, non-significant positive slope and significant positive slope respectively.

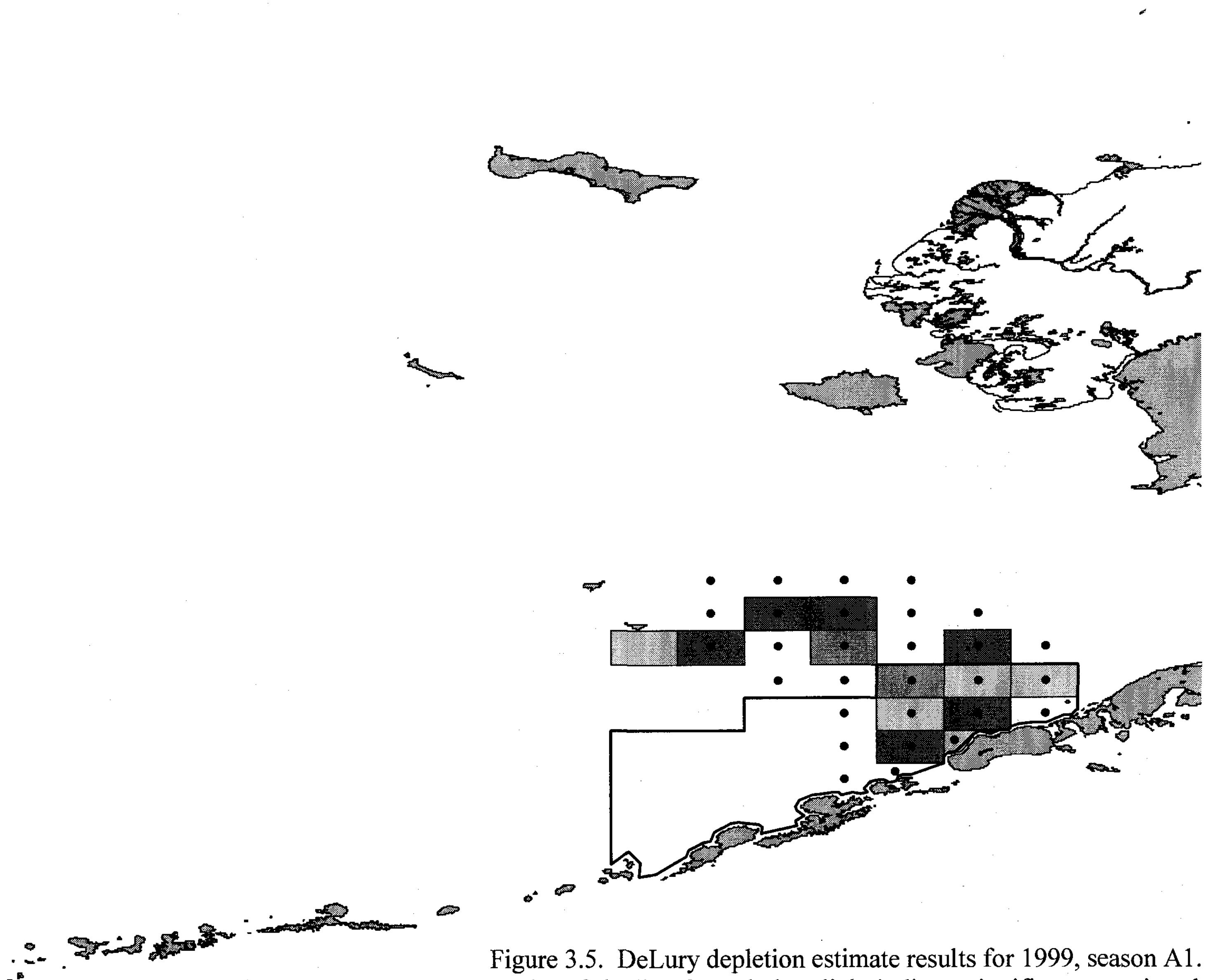


Figure 3.5. DeLury depletion estimate results for 1999, season A1. Four grades of shading from dark to light indicate significant negative slope (significant depletion), non-significant negative slope, non-significant positive slope and significant positive slope respectively.

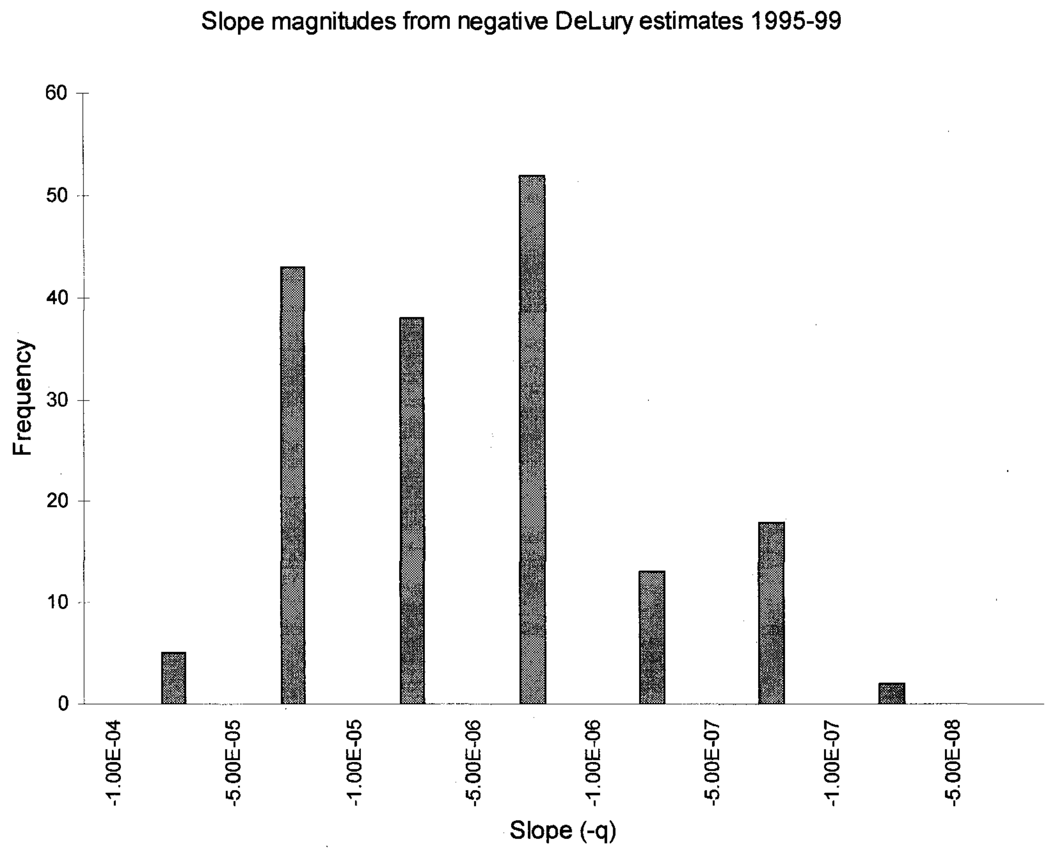


Figure 3.6. Distribution of negative estimates of catchability from the DeLury depletion estimators.

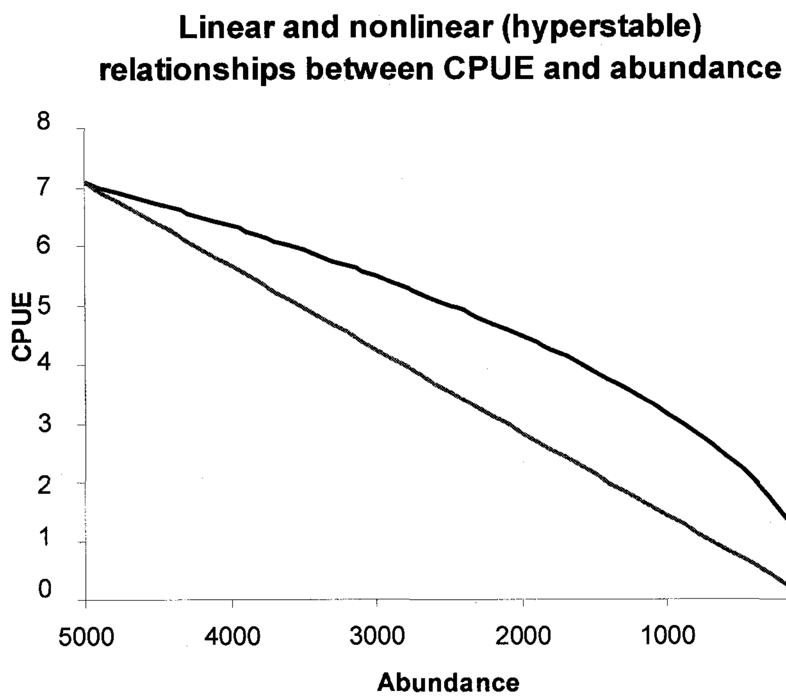
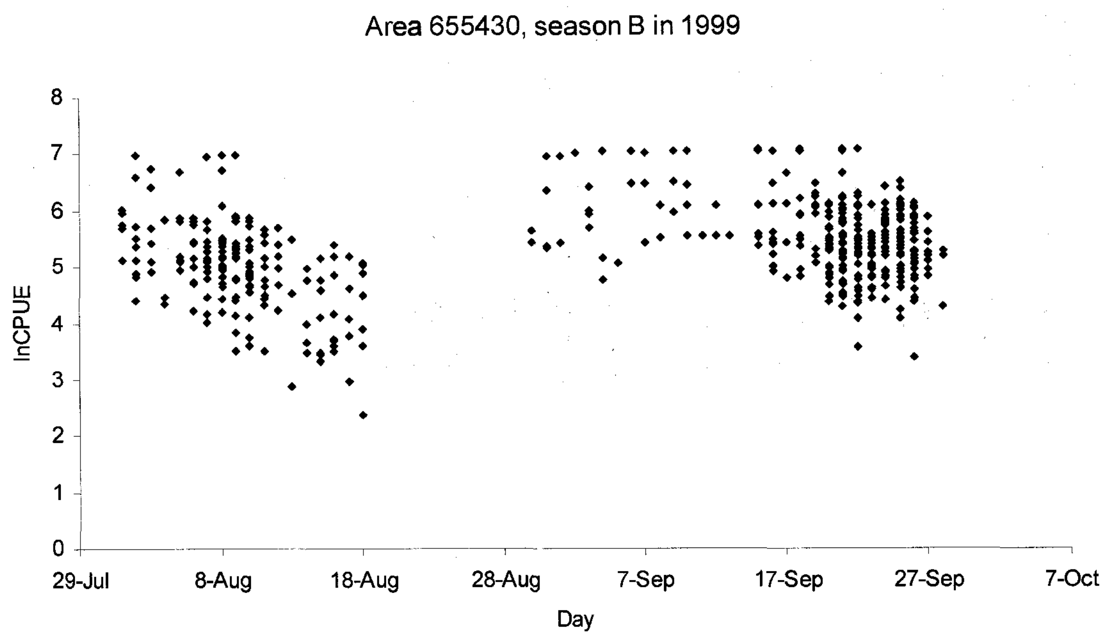


Figure 3.7. Graphical description of a hyperstable (dark) CPUE relative to abundance versus a purely linear relationship (light). Note that with the hyperstable relationship, CPUE drops relatively quickly at low abundances and relatively slowly at high abundances making depletion easier to detect at low abundances and more difficult at higher abundance.



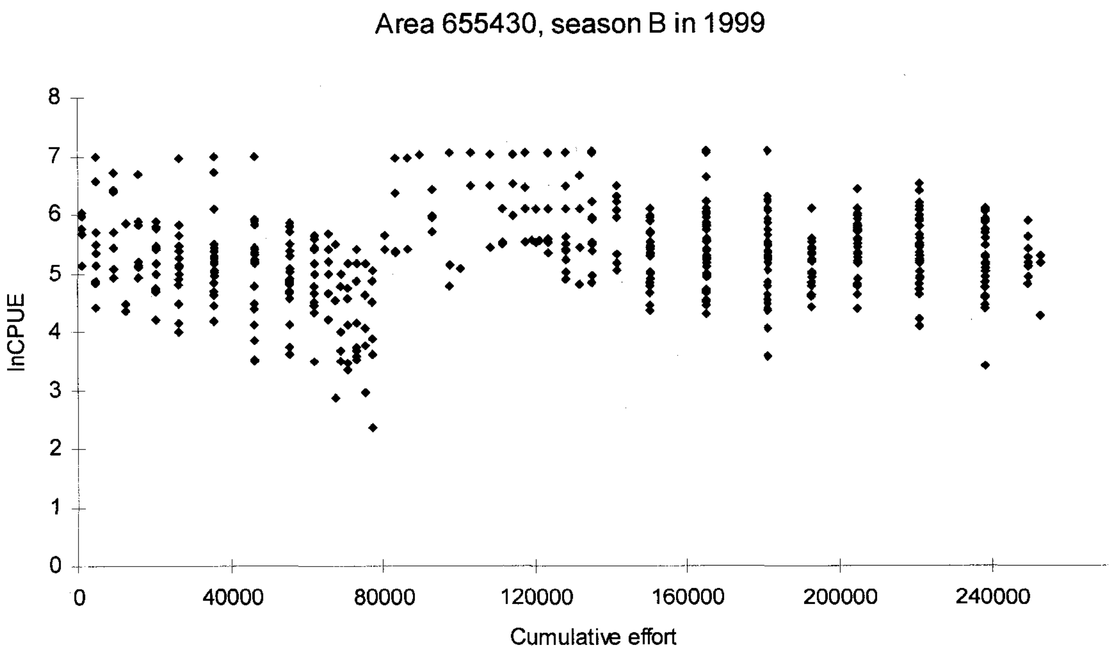


Figure 3.8. Scatter plot of lnCPUE over time (top) and effort (bottom) showing one distinct period of depletion separated by a 2 week period of no exploitation followed by two weeks of light exploitation pressure followed by another period indicating depletion.

CHAPTER 4

Hierarchical spatial Bayesian analysis of a DeLury depletion estimator for walleye pollock (*Theragra chalcogramma*) in the eastern Bering Sea[4]

Brian C. Battaile, Terrance J. Quinn II, and Milo D. Adkison

Abstract

A hierarchical spatial Bayesian model was applied to a DeLury depletion estimator of the walleye pollock fishery in the eastern Bering Sea. Spatial covariates and a conditional autocorrelation (CAR) structure were individually added to the basic hierarchical model and then combined in a final model. Results were compared to "frequentist" DeLury depletion estimates of the same data set and were not appreciably different. The number of areas with significant depletion changed by only 1-3, of 153 strata, for each of the 4 models, and estimated variability of catchability was not significantly different between the Bayes and frequentist models. The posterior probabilities of the spatial covariates were centered about zero and the CAR spatial covariates did not significantly change parameter estimates of the intercept, indicating that the spatial covariates used could not predict the spatial pattern of depletion and that very little evidence for spatial autocorrelation existed using the available CAR parameterization. Therefore, our analysis has extracted the major signals contained in the CPUE data regarding depletion.

4.1 Introduction

Bayesian modeling has become a popular tool for fisheries biologists in the last decade because its capability to properly express uncertainty in both population

[4] To be submitted to Canadian Journal of Fisheries and Aquatic Sciences

parameters and data inputs. In particular, hierarchical Bayesian models have proved to be particularly useful by providing insight at the meta-population scale (Liermann and Hilborn 1997; Harley and Myers 2001; Miller and Methot 2002) and by improving estimates in fisheries where data quality is poor (Su et al. 2001; Adkison and Su 2001).

Hierarchical models, for a collection of populations, assume that particular population parameters can be described sufficiently by an empirical umbrella distribution (normally Gaussian). The populations that then make up a level of the hierarchical structure "draw" their realization of the population parameter in question from the umbrella distribution. This process provides insight into the meta-population characteristics via the umbrella distribution and provides reasonable structure to populations that may have poor data about the parameters of interest. Such models have clear application to fisheries problems for which considerations of ecosystem wide impacts are becoming important to fisheries managers and for which data quality is poor from either historic databases or limitations on future data collections.

Hierarchical Bayesian models naturally lend themselves to spatial modeling, in which the entire area of interest can be subdivided to provide a hierarchical structure. Spatial modeling has been used in fisheries work, and most often in spatial prediction such as kriging (e.g., Sullivan 1991), in which a grid of survey hauls are used to extrapolate a map of continuous abundances. In its most basic form, spatial modeling requires estimating the spatial correlation between areas of a study site. This structure is then used for spatial prediction or removed to satisfy assumptions when used in generalized linear models relating the spatial data to other covariates of interest. The latter is our focus here and can be used in conjunction with Bayesian techniques.

One goal here is to introduce the fisheries community to spatial Bayesian techniques (recently investigated by Wyatt (2003)), using data from and motivated by the pollock fishery and its potential interaction with the endangered Steller sea lion. Cressie (1993) is the standard reference on spatial modeling for the mathematically inclined and numerous introductory texts have also been produced (e.g., Bailey and Gatrell 1995; Fotheringham et al. 2000) and some of the major statistical packages now offer spatial modules. Considerable work in this area has been undertaken, motivated almost entirely by epidemiology (Clayton and Kaldor 1987; Cressie and Chan 1989; Besag et al. 1991). The spatial study of disease rates, patterns, and associated covariates is easily translated into fisheries applications of catch rates, stock densities, and the myriad of covariates that may affect them.

Our previous work (Battaile and Quinn, in review, chapter 3) focused on using the DeLury depletion estimator with fishery CPUE data to determine if statistically detectable depletion occurred in the pollock fishery; because the pollock fishery has been strictly regulated since 1999 after being implicated in possibly contributing to the decline of the Steller sea lion via food competition (NRC 2003). The analysis was implemented in a general linear model setting using data stratified by space and time. The separate DeLury model estimates were investigated further using GLM models in an attempt to relate environmental and spatial variables thought to be important to the endangered Steller sea lion, pollock fishery, and their interaction. These post hoc analyses revealed that depletion tended to be greatest in areas of lowest effort, catch, and estimated initial biomass, and that depletion tended to be greatest nearest the islands. Our second goal here is meant to further unify the analysis and gain additional perspective through the use of Bayesian spatial statistical techniques. We wish to determine if patterns of depletion have a spatial connection and whether the resultant spatial relationship alters the estimation and/or interpretation of the depletion parameters. In addition we hope to gain a more general understanding of the processes regulating the Bering Sea pollock population through the spatial hierarchy of the Bayesian analysis.

4.2 Materials and Methods

Our analysis begins with the results of DeLury depletion analysis of selected Alaska Department of Fish and Game (ADF&G) reporting areas in the eastern Bering Sea (Battaile and Quinn chapter 3). These results are now used in a hierarchical Bayesian framework using space as the hierarchical structure, so that individual ADF&G areas are assumed to have parameter values (specifically the catchability of pollock) that come from a common parametric distribution. We stratify the analysis by time so that different seasons and years are analyzed separately, so that one stratum consists of one ADF&G area from one season in one year. We are also interested in the potential spatial structure of depletion and what spatial covariates may affect depletion. The spatial correlation can be modeled using the conditional autoregressive (CAR) function to model the spatial dependence in the catchability or logarithm of initial biomass. To the CAR model we add covariates to attempt to explain the spatial pattern of depletion via geographic and environmental variables.

4.2.1 DeLury depletion model

The catch and effort data available for our depletion estimator includes catch by weight in kilograms and fishery effort, measured as haul time in minutes, which were standardized for vessel and fishery related differences (Battaile and Quinn, 2004). ADF&G areas that were chosen for analysis were within or near the Steller sea lion Critical Habitat/Catcher Vessel Operation Area (CHCVOA) (Figure 1). The areas were stratified by season (A or B except in 1999 when the seasons were stratified into A1, A2, B and C) and five years from 1995-1999 for a total of 153 strata. The basic form of the DeLury estimator (DeLury, 1947) is,

(1) $\ln U_t = \ln(qB_0) - qE_t$,

in which U_t is the catch-per-unit-effort (CPUE), B_0 is the initial biomass, E_t is cumulative effort over time, and q is the coefficient of catchability (Seber 1982). The effort data are assumed to be measured without error because of the large observer program for the fishery. Equation 1 is in the form of a linear regression where $\ln(qB_0)$ is the intercept and the slope is q, which, if found to be significantly negative, would indicate depletion.

Natural mortality M is incorporated, with each area indexed by i, such that

(2) $\ln U_{i,t} = \ln\lfloor q_i B_{i,0} \rfloor - q_i E_{i,t} - M_i t + \varepsilon_{i,t}$,

(Battaile and Quinn, chapter 3). M is assumed to be constant at 0.3, as estimated by the pollock stock assessment (Ianelli et al, 2003). Details of this model are found in (Battaile and Quinn, chapter 3).

4.2.2 Bayesian model

The catchability coefficient q is the parameter of primary interest. While some variation from region to region is expected in the catchability due to age, size, and spawning behavior, it is reasonable to assume that catchability within a single ADF&G region is constant, and that catchability over the entire eastern Bering sea would vary but can be adequately described via a normal distribution.

We use the conventional assumption that the error in lnCPUE is normally distributed, so that

(3) $\varepsilon_{i,t} \sim N(0,\sigma^2)$.

In this model the variance, σ^2, is assumed to be equal across areas. Catchability is modeled as

(4) $q_i \sim N(\mu,\sigma_q^2)$.

"Hyper priors" are required for all parameters of the empirical distributions describing model parameters. The hyper priors describe our best guess for the range of possible values the parameters might take. Since q tends to be quite small, ~–0.0002, a normal distribution that is diffuse around 0 provides a prior for the q_i's; the choice of

(5) $\mu \sim N(0,1)$,

provides an essentially uniform probability density at 0.4 over the range of –0.1 to 0.1. B_0 can also be estimated as a function of the intercept b_0 (b_0=log(qB_0)) which will be treated similarly to q_i such that

(6) $b_{0,i} \sim N(\mu_{b,i},\sigma_b^2)$,

with hyper prior

(7) $\mu_b \sim Unif(0,10)$.

which is a proper and uninformative prior covering the probable values of μ_b based on the frequentist results of chapter 3. We select "proper" priors to ensure a finite posterior probability distribution of the parameters (Su et al. 2001). For ease of calculation and interpretability of the posterior, a conjugate prior is chosen for the variances σ^2, σ^2_q, and σ^2_b with diffuse parameter values. The inverse gamma distribution fulfills these requirements. However, our software uses the precision (τ), defined as the inverse of the variance, in its calculations. Therefore we use the gamma distribution as a prior for the three τ parameters:

(6) $\tau_q \sim G(0.001, 0.001)$,

(7) $\tau \sim G(0.001, 0.001)$,

(8) $\tau_b \sim G(0.001, 0.001)$.

(Figure 2). The variances σ^2, σ^2_q, and σ^2_b are then calculated as $1/\tau$, $1/\tau_q$, and $1/\tau_b$, respectively.

The model parameters to be estimated are the q_i's, the $b_{0,i}$'s and the variance of the data, σ^2. The hyper parameters to be estimated are σ^2_q, σ^2_b, μ_q and μ_b. The final joint posterior distribution is

(11)
$$\begin{gathered} p(q_i, b_{0,i}, \sigma^2, \sigma_q^2, \mu, \sigma_b^2, \mu_b | D) \propto p(\sigma_q^2, \mu_q) p(\mu_b, \sigma_b^2) p(\sigma^2) \\ \prod_{i=1}^{I} N(b_{0,i} | \mu_b, \sigma_b^2) \prod_{i=1}^{I} N(q_i | \mu, \sigma_q^2) \prod_{t=1}^{n_i} N(\ln CPUE_{i,t} | E_t, M, q_i, b_{0,i}, \sigma^2) \end{gathered}.$$

4.2.3 Spatial structure

While the Bayesian approach assumes spatial similarity to some degree in its assumption that the catchabilities come from a common parametric distribution, spatial modeling assumes a smaller scale correlation so that areas next to each other are more similar than areas that are farther away from each other. When areas are correlated based upon their spatial distribution, the assumption of independence is violated in statistical applications. Overstated confidence in estimated variability results, which should be corrected. It is reasonable to expect that some spatial correlation exists in ln CPUE estimates among ADF&G reporting areas in the eastern Bering Sea. Spatial correlation can be accounted for by using known covariates, directly modeled, or both.

Explaining spatial correlation through the use of known covariates is simply accomplished by adding covariates to the basic regression model. For example, the DeLury equation from (2) becomes

$$(12) \qquad \ln U_{i,t} = \ln\lfloor b_{0,i} \rfloor - q_i E_{i,t} - M_i t + \beta_1 x_1 + \beta_2 x_2 .... + \varepsilon_{i,t} .$$

After fitting this extended model, the residuals are examined for any remaining spatial correlation via variograms or related methods. Covariates are removed or added until an appropriately parsimonious and explanatory equation is developed. The added advantage to this method is that the spatial correlation is explainable with biologically meaningful covariates.

The correlation between areas may also be directly modeled. The appropriate methodology depends upon the spatial structure of the data. Conventionally, the correlation between all possible pairs of points is modeled with the highest correlation at zero distance between two points and then successively lower correlation values, tailing off to zero as the distance between two points approaches infinity. However, the spatial structure may instead consist of lattice networks or grids (such as crop plots) for which the unknown estimators of interest are means (or other functions of the data) of some measurable quantity over a plot within the grid. Then, the correlation structure takes a discrete form such that only bordering areas influence each other. The degree to which directly bordering areas and areas further away are affected can take many different forms. The WinBUGS program provides variants of these models and others. Because our depletion estimators are laid out in a grid (Figure 3), the discrete formulation is more applicable than a continuous distance formulation.

The variance-covariance matrix of the variable of interest is what is estimated to account for the spatial correlation. The conditional autoregressive model provided by WinBUGS uses a covariance matrix of the form

(13) $$\Sigma = (\mathbf{I} - \rho\mathbf{C})^{-1}\mathbf{M},$$

in which **I** is the identity matrix, ρ is a scalar determining the overall strength of the spatial correlation, **C** is the weighting matrix giving the relative influence that area a_i has on adjacent areas, and **M** is a diagonal matrix showing the relative influence that adjacent areas have on area a_i. If n_i is the number of adjacent areas to area a_i, then C and M are filled in by $1/n_i$ (e.g., Figure 4). The intrinsic formulation of the model allows only directly adjacent areas to have influence and for ρ to be set to its maximum, which in this case is 1.

WinBUGS parameterizes its spatial dependence as an overall intercept (α) plus area-specific coefficients (γ_i) which sum to zero. Our initial parameterization is then

(14) $$\ln U_{i,t} = \ln[b0_i] - q_i E_{i,t} - M_i t + \alpha + \gamma_i + \varepsilon_{i,t}, \sum_i \gamma_i = 0,$$

to which covariates can be added in as in (12). To avoid a confounding affect between α, γ_i, and the intercept log[b_{0i}], we set the intercept equal to zero so that the γ_i's include all variability due to the different spatial areas, including both unknown random effects and spatial autocorrelation. This change of course requires the removal of the priors associated with the intercept as well. The sum $\gamma_i + \alpha$ is a quantity similar to the intercept in equation 2 but with the spatial autocorrelation, we term this $\alpha\gamma_i$. Thus the fitted model is

(15) $$\ln U_{i,t} = \alpha\gamma_i - q_i E_{i,t} - M_i t + \varepsilon_{i,t}, \sum_i \gamma_i = 0.$$

WinBUGS requires the use of an improper flat prior over the entire real line for α and the WinBUGS spatial manual authors (Thomas et al. 2004) recommend a prior for the inverse of σ as

(16) $$\tau_{car} \sim G(0.5, 0.0005).$$

We examined 4 different models. The base model is a Bayesian treatment of the areas with no spatial modeling and no spatial covariates. For the second, spatial covariates are added to the base model. For the third, the CAR parameterization is added to model one. For the fourth, covariates are added to model 3. The four covariates we use are total catch (x_1), total effort (x_2), whether an area is in the CHCVOA (areas south of the heavy line in figures 1 and 3) or not (x_3), and whether or not at least 50% of an

ADF&G area is within the Bering Sea Pollock Restriction Area (BSPRA) (x_4), which is closed to fishing, and includes four areas 665401, 655409, 645434, and 635502. These covariates were found to be the most important in the frequentist analysis of chapter 3. Appendix 4.1 contains the winBUGS code for each of these models and starting values for the three MCMC chains.

4.3 Results

For all 4 of the Bayesian models, the depletion results were very similar to the frequentist DeLury model. We compare the two by looking to see if 97.5% of the probability of the posterior distribution of q is on one side or another of 0. This roughly compares to a finding of significance for the frequentist model. We use year/season 1995B for illustration throughout and Figure 5 shoes the strata with sufficient data for analysis. Box plots of estimated q_i's from model 1 for 1995B indicate the median varies relative to zero across the strata but that most tend to be positive (indicating depletion) (Figure 6). We classified results into 4 categories based on the sign and significance of the slope. Of the 153 models using the frequentist method, 75 did not find any significant depletion, 16 showed a significant increase in lnCPUE, and 62 indicated significant depletion. For each Bayesian model type, only between 17 and 23 strata of the 153 changed and generally about half of these changed from one non-significant slope sign to the other. The net change of significant and non-significant slopes and signs over a model was very small (2-5) relative to the frequentist results (Table 1).

One advantage of Bayesian modeling is that the variability estimates can be reduced if some areas have weak data due to outliers or high variability. The differences between the frequentist and the Bayes estimates of catchability and associated standard error tended to be larger for strata with smaller data sets (Figure 7). However, using the difference between the frequentist and the Bayesian model standard error estimates of the catchability q, as a percentage of the frequentist standard error, the median difference of the 4 Bayesian models was –0.002%, –0.010%, –0.023%, and –0.021% and the geometric means of the same data were –0.048%, –0.048%, –0.081%, and –0.064% indicating that the standard error for the Bayesian models was slightly larger. Statistically, however, no difference between the frequentist and Bayesian standard errors is detectable using a standard t-test in which years and seasons are pooled together(n=153, Model 1 p=0.48, Model 2 p=0.49, Model 3 p=0.26, Model 4 p=0.25).

The posterior distributions of the primary variables including the slope, intercept, CAR model "intercept" and their estimated priors exhibit typical normal distributions. The mean of q (μq) prior (Figure 8) is centered about 0 with a relatively dispersed distribution compared to the q values themselves. The distributions of $\alpha 0$ of models 3 and 4 (Figure 9) and the intercept of models 1 and 2 (Figure 10) are centered near values of 5-6 and there similarity indicates equivalent roles in the different model. Spatial parameters tended to be centered around 0 with relatively large standard errors so that the probability density of the coefficient is well dispersed on either side of 0 (Figure 11). Only β_3 and β_4 from 1999C had greater than 97.5% of their probability mass different from zero, which occurred for both models 2 and 4. There is virtually no difference between the intercepts of models 1 and 2 and the CAR model equivalents of models 3 and 4 indicating that no spatial autocorrelation of the CAR form exists (Figure 12) (see also the Appendix 4.1 for all estimated variables for 1995B, models 1-4). The differences in the box plots in Figure 12 are due to models 2 and 4 having spatial covariates while 1 and 3 do not.

4.4 Discussion

The objectives of using Bayesian methodology are to spatially unify the analysis which ought to result in reduced variability estimates of parameters, strengthening of estimates in areas of weak data, and characterization of the spatial structure of fishery related depletion in the eastern Bering Sea walleye pollock population. Because the number of data points for an area varies between 30 and 2500, the areas with larger data sets could have influenced the results of areas with smaller data sets, but the overall effect was minor. As expected, the differences between the frequentist and Bayes methods of the standard error estimates and estimates of catchability q did increase as the number of data points for a stratum decreased, indicating that the hierarchical methods affected the results of the areas with less data. Despite this, there were not large differences between the frequentist results and the four Bayesian models investigated here. Variability about the catchability q was not reduced; in fact it increased by approximately 5% for each of the four models. Though this reduction is not statistically significant, it may be an indication of the increased number of variables estimated in the Bayesian models. In addition, there was very little difference in the number of areas that showed large percentages of their probability densities different from 0 in the Bayesian models, relative to the numbers of areas in the frequentist model indicating significant depletion.

The reason for the general similarity between the Bayesian and frequentist results is probably due to the quality of the data. The data were thoroughly inspected to remove outliers prior to either the frequentist or Bayesian treatments as described in Battaile and Quinn (2004 and in review). Hence, the frequentist models were not adversely affected by highly variable data and the Bayesian models did not have anything to "reign in". Even the strata with the smallest number of observations (30) are not necessarily weak, as this is an enviable sample size for many data poor studies.

The posterior distribution of μ_q was larger than what we would initially expect given the size of the q_i's (typically in the 10^{-5} to 10^{-6} range), as the 95% confidence interval tended to range between −0.005 to 0.005. The q_i's are often quite variable ranging between 3 orders of magnitude and on either side of zero for the areas within a season, though the largest catchability in absolute terms was of the order 10^{-4}. We explored the sensitivity of the prior by using one with a variance 3 orders of magnitude smaller than that used in equation 5. We also eliminated area 14 in a separate model run because it's estimate of q is much smaller than the typical values. No change in the posterior to these two model alterations is detectable indicating that the results for μ_q are robust across model assumptions.

There is very little evidence for spatial autocorrelation of the CAR form in the parameter estimates of catchability or initial biomass over the eastern Bering Sea. Because the posterior densities of the β's usually covered zero, there is little evidence that the spatial covariates explain the variability in catchability or initial biomass either (e.g., Figure 11). Our models 3 and 4 do not specifically parameterize for area specific unknown random differences and separate spatial autocorrelation, instead these to are combined in our model. However, because the b_{0i} and $a\gamma_i$ parameter and associated variability estimates are essentially the same when comparing model 1 to 3 and 2 to 4, we can conclude that the CAR model does not add to the explanatory power of the models (Figure 12).

The structure of the CAR model may not fit the potential spatial autocorrelation structure that exists for this data. The parameter ρ is set to its maximum of one, which may not be best for this data set, but the software did not permit other choices for this model. In addition, only areas directly adjacent to area a_i can influence it, whereas more sophisticated models can produce influences that decrease as the distance from area a_i decreases. Hence, if spatial autocorrelation exists, it may not exist in the stringent form we modeled.

If a spatial structure does exist, it may also be that it does not follow our spatial scale. Ideally, our spatial sampling unit should be somewhat smaller than the natural spatial structure. The ADF&G areas may be larger or of a similar size of any spatial structure that exists. In that case, the ADF&G areas may bisect more natural boundaries, there by fragmenting the natural spatial structure and pooling portions together that are not similar. This potential for variability within the sampling units would likely work to hide any effects of depletion as the CPUE in one corner of the area could be very different from that in the opposite corner ~45 nm away. There are also, on average, only 12 to 13 areas for each model, which may be too small a sample size to detect spatial autocorrelation. Despite this, the data still strongly indicate a depletion effect, which suggests that depletion is a consistently occurring phenomenon in the eastern Bering sea.

The Bayesian methods certainly reinforce the results found in chapter 3, that the eastern Bering Sea walleye pollock population is experiencing statistically significant amounts of fishery induced depletion, and that little spatial autocorrelation is present in the data at the scale and form we worked in. It appears that we extracted most if not all of the information about depletion out of the data from the frequentist method. Further research could include expanding the hierarchical structure to include temporal levels such as seasons or years. In addition, alternative parameterizations of the CAR model may be better suited to this data set.

4.4.1 Acknowledgements

This publication is the result of research sponsored by Alaska Sea Grant with funds from the National Oceanic and Atmospheric Administration Offices of Sea Grant, Department of Commerce, under grant no. NA 86RG0050 (project no. R/101-02) and from the University of Alaska with funds appropriated by the state.

4.5 References

Adkison, M.D. and Su, Z. 2001. A comparison of salmon escapement estimates using a hierarchical Bayesian approach versus separate maximum likelihood estimation of each year's return. Can. J. Fish. Aquat. Sci.**58**: 1663-1671.

Battaile, BC. and Quinn, T.Q. 2004. Catch per unit effort standardization of the eastern Bering Sea walleye pollock (*Theragra chalcogramma*) fleet. Fish. Res. **70**: 161-177.

Battaile, B.C. and Quinn, T.Q. *in review*. A DeLury depletion estimator for walleye pollock (*Theragra chalcogramma*) in the eastern Bering Sea.

Besag, J., York, J., and Mollie, A. 1991. Bayesian image restoration, with two applications in spatial statistics. Ann. Inst. Statist. Math. **43**: 1-59.

Bailey, T. C. and Gatrell, A.C. 1995. Interactive spatial data analysis. New York. Person Education.

Clayton, D., and Kaldor, J. 1987. Empirical Bayes estimates of ate-standardized relative risks for use in disease mapping. Biometrics, **43**: 671-681.

Cressie, N. 1993. Statistics for spatial data. New York: Wiley.

Cressie, N., and Chan, N.H. 1989. Spatial modeling of regional variables. J. Amer. Stat. Ass. **84**: 393-401.

DeLury, D.B. 1947. On the estimation of biological populations. Biometrics. **3**: 145-167.

Fotheringham, A.S., Brunsdon, C., and Charlton, M. 2000. Quantitative Geography: Perspectives on spatial data analysis. Thousand Oaks. Sage Publications.

Harley, S.J., and Myers, R.A. 2001. Hierarchical Bayesian models of length-specific catchability of research trawl surveys. Can. J. fish. Aquat. Sci. **58**: 1569-1584.

Liermann, M., and Hilborn, R. 1997. Depensation in fish stocks: a hierarchic Bayesian meta-analysis. Can. J. Fish. Aquat. Sci. **54**: 1976-1984.

Miller, R.B., and Methot, R.D. 2002. Are-structured meta-analysis of U.S. west coast rockfish (Scorpaenidae) populations and hierarchical modeling of trawl survey catchabilities. Can. J. Fish. Aquat. Sci. **59**: 383-392.

National Research Councel (NRC). 2003. Decline of the Steller sea lion in Alaskan waters. Untangling food webs and fishing nets. National Academy Press, Washington D.C. 204p.

Su., Z., Adkison, M.D., and Van Alen, B.D. 2001. A hierarchical Bayesian model for estimating historical salmon escapement and escapement timing. Can. J. Fish. Aquat. Sci. **58**: 1648-1662.

Sullivan, P.J. 1991. Stock abundance estimation using depth-dependent trends and spatially correlated variation. Can. J. fish. Aquat. Sci. **48**: 1691-1703.

Thomas, A., Best, N., Lunn, D., Arnold, R., and Spiegelhalter, D. 2004. GeoBUGS user manual. http://www.mrc-bsu.cam.ac.uk/bugs

Wyatt, R.J. 2003. Mapping the abundance of riverine fish population; integrating hierarchical Bayesian models with a geographic information system (GIS). Can. J. Fish. Aquat. Sci. **60**: 997-1006.

Table 4.1. Number of q_i's for each model, out of 153, that were non significant, significant negative or significant positive (from a frequentist perspective using 2.5 and 97.5% probability).

		Model			
	Frequentist	1	2	3	4
Non-significant slope	75	77	78	79	80
Significant positive slope	16	15	14	15	14
Significant negative slope	62	61	61	59	59
non-sig pos to non-sig neg		3	3	5	5
non-sig neg to non-sig pos		5	5	6	4
non-sig neg to sig neg		3	3	3	3
non-sig pos to sig pos		1		1	
sig neg to non-sig neg		4	4	6	6
sig pos to non-sig pos		2		2	1
sig pos to non-sig neg			2		1

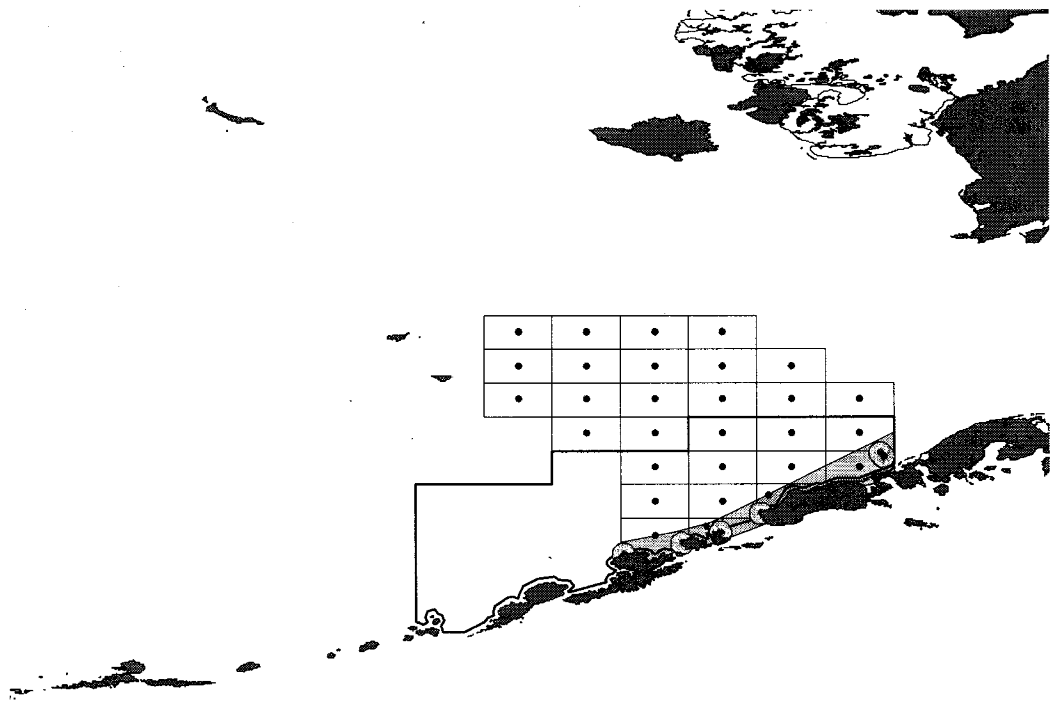


Figure 4.1. Map of the Eastern Bering sea detailing the 29 Alaska Department of Fish and Game reporting areas (rectangles) in and around the Critical Habitat/Catcher Vessel Operational Area (outlined in the dark line).

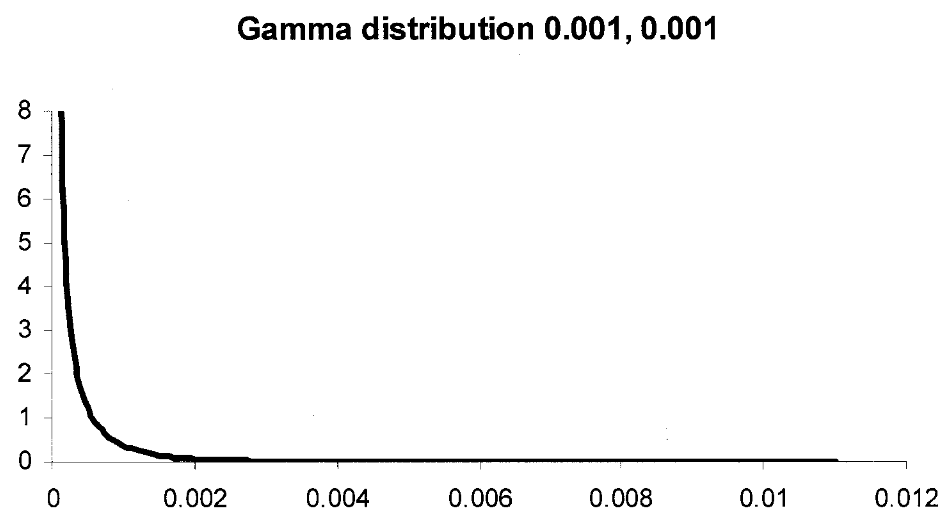


Figure 4.2. Gamma probability density with parameters (0.001, 0.001).

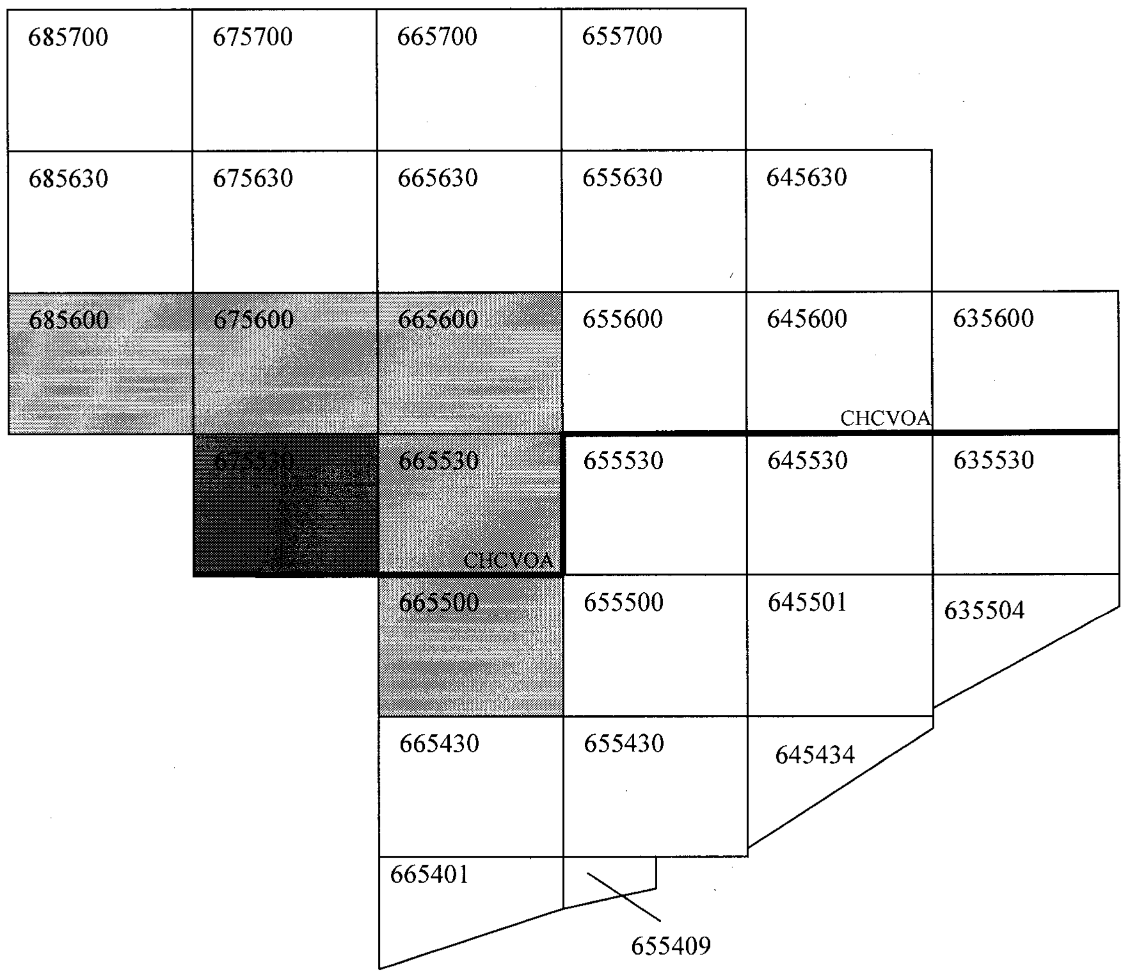
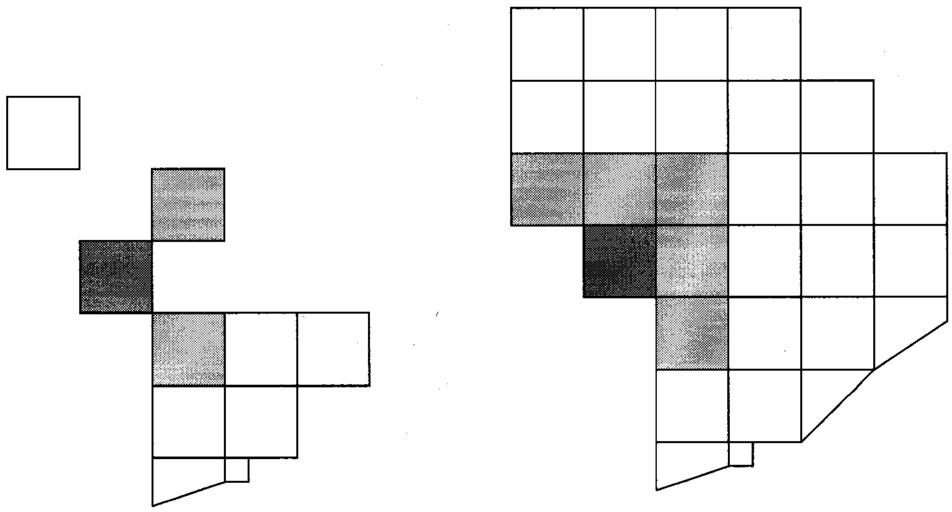


Figure 4.3. Rough map of the 29 reporting areas using Alaska Department of Fish and Game areas, depicting what are considered adjacent areas (light gray shading) to area 675530 (dark gray shading).



W

1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.50	0.50	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.25	0.00	0.00	0.25	0.00	0.25	0.25	0.00	0.00
5	0.00	0.00	0.00	0.20	0.00	0.20	0.20	0.20	0.20	0.00
6	0.00	0.00	0.00	0.00	0.33	0.00	0.33	0.33	0.00	0.00
7	0.00	0.00	0.00	0.25	0.25	0.00	0.00	0.25	0.00	0.25
8	0.00	0.00	0.00	0.17	0.17	0.17	0.17	0.00	0.17	0.17
9	0.00	0.00	0.00	0.00	0.33	0.33	0.00	0.33	0.00	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.50	0.00	0.00

M

1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00
8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.00
9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50

Figure 4.4. Ten hypothetical areas selected for analysis (upper left) because of adequate data requirements, from the 29 potential areas in and around the Critical Habitat/Catcher Vessel Operational Area. The W and M matrices for the 10 areas numbered 1-10 in the matrices starting in the top left counting down a column and then across a row such that the darkest area is area 2 and the two adjacent areas to area 2 are 3 and 4 in the matrices.

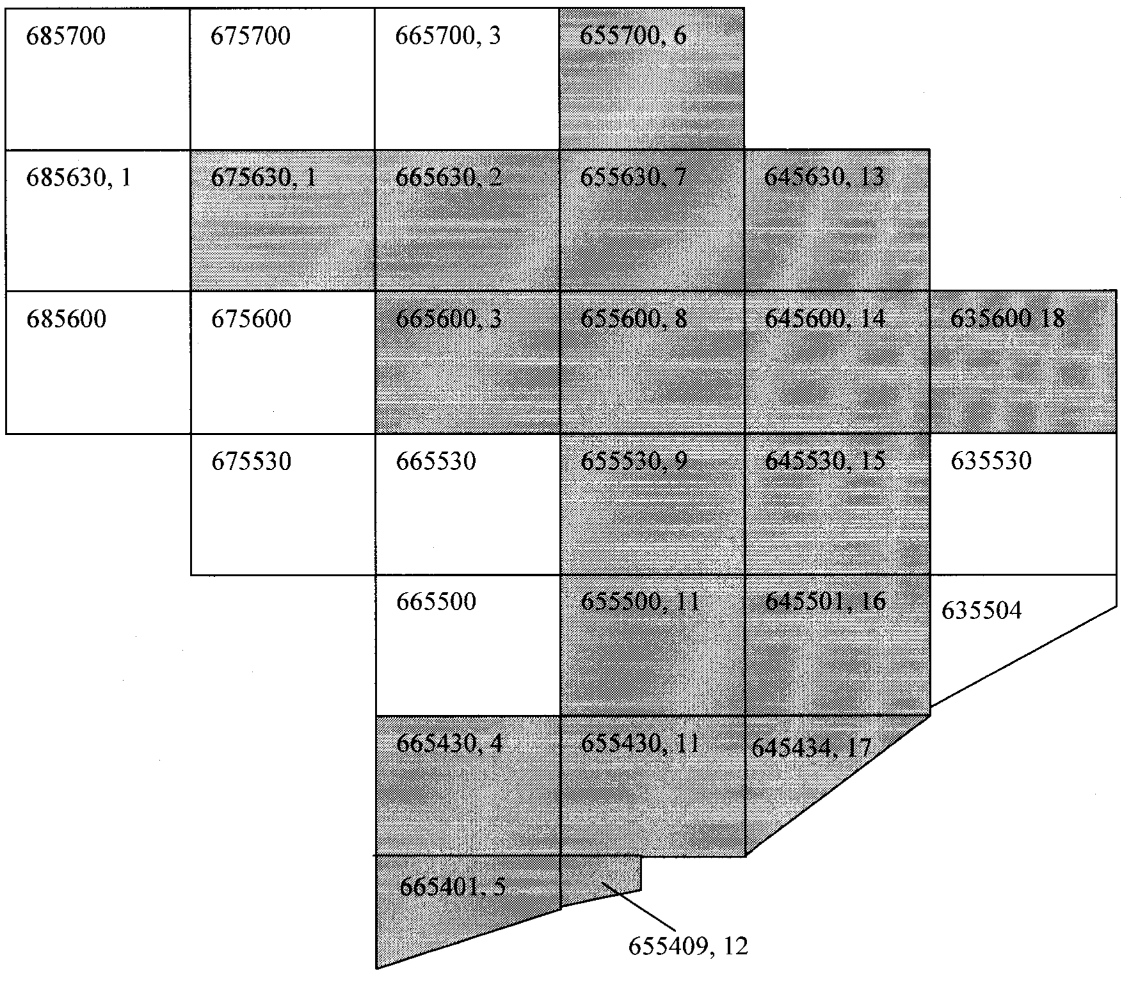


Figure 4.5. 18 areas for year/season 1995B (shaded and numbered) with sufficient data for analysis.

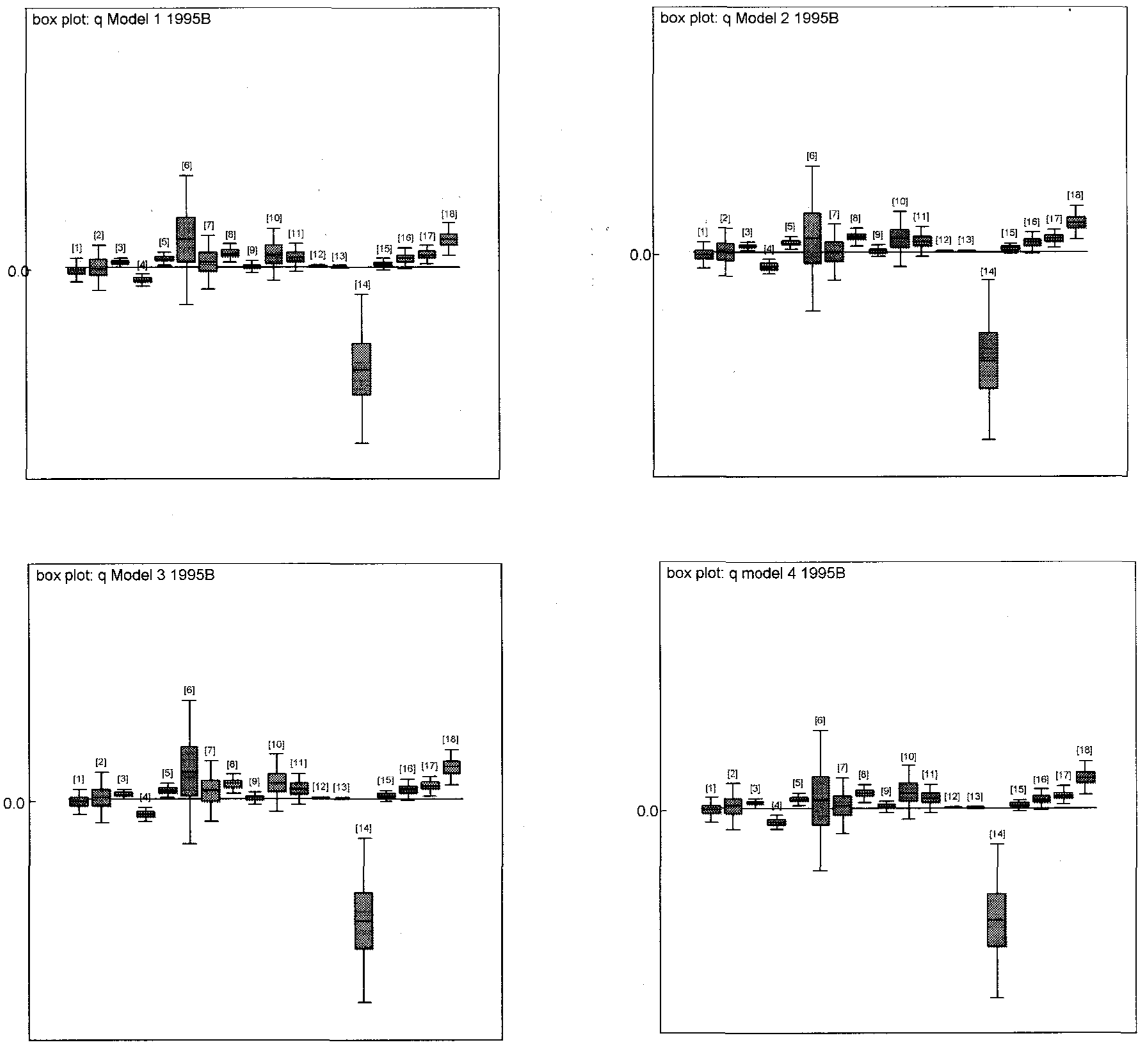
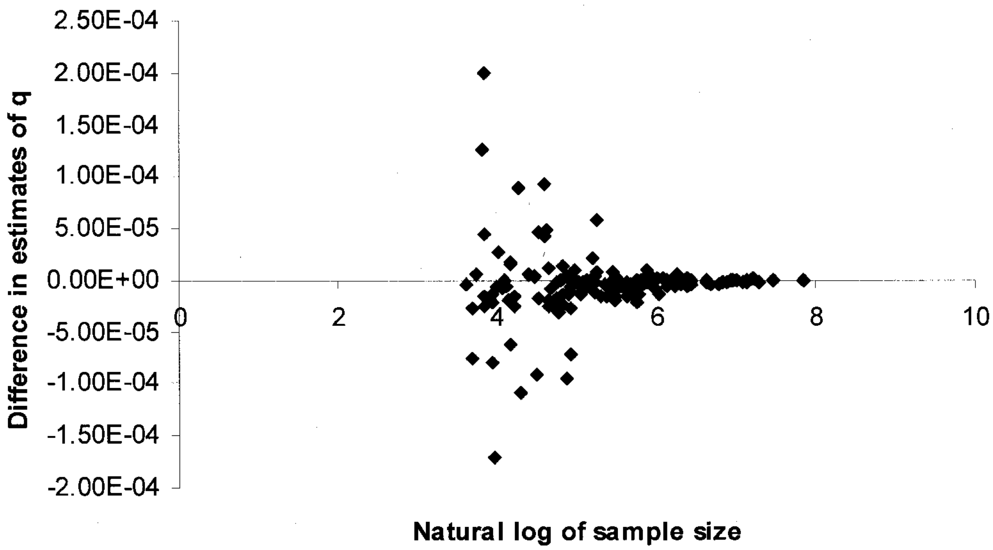


Figure 4.6. Box plots of estimated q_i's for Models 1-4 strata 1995B. Boxes indicate the inter-quartile range while the arms indicate the 2.5% and 97.5% probability limits.



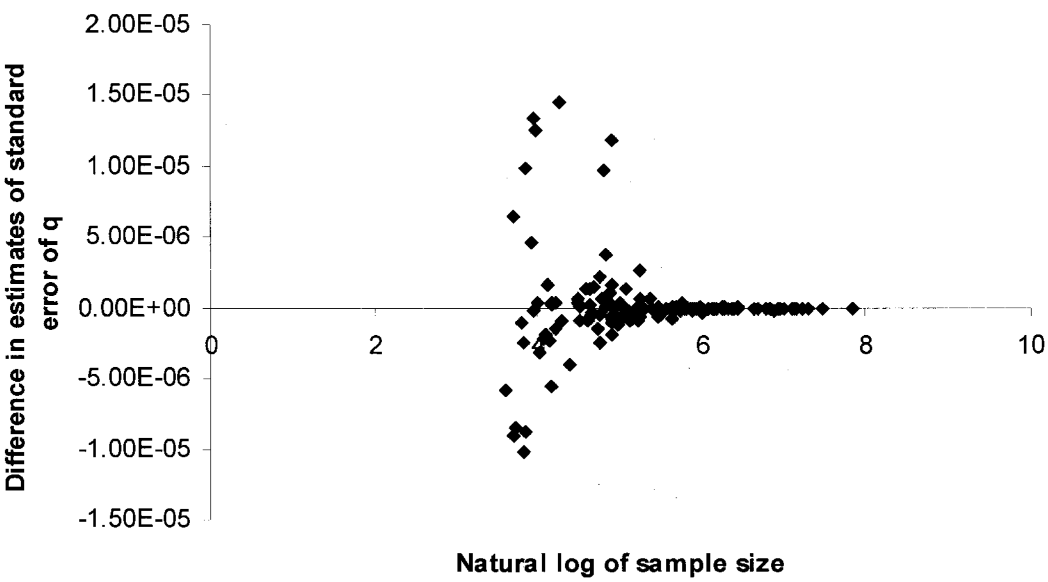


Figure 4.7. Differences between frequentist and Bayesian (frequentist minus Bayes) model 3 estimates of catchability q and its associated standard estimates relative to the log of the number of data points in a strata using model 3 results.

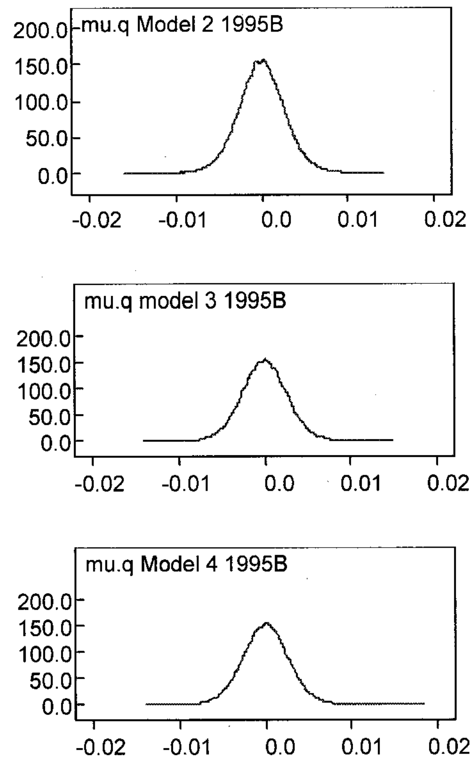
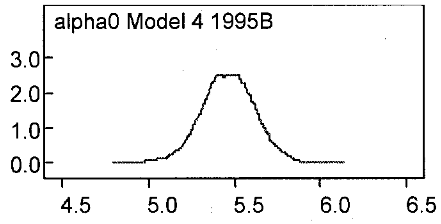


Figure 4.8. Posterior density of μ_q for models 1, 2, 3, and 4, year/season 1995B.



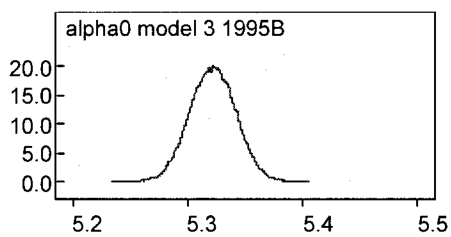


Figure 4.9. Posterior density of $\alpha 0$ for models 3 and 4, year/season 1995B.

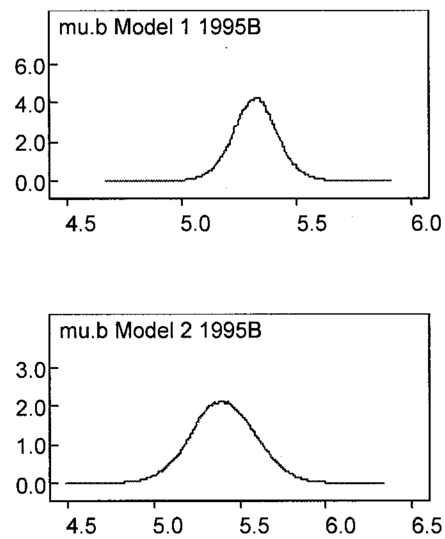
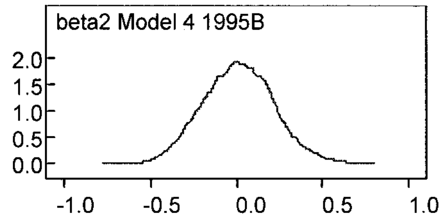


Figure 4.10. Posterior density of μ_b for models 1 and 2, year/season 1995B.



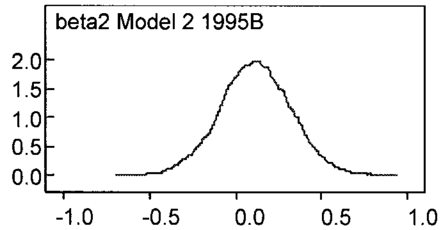


Figure 4.11. Posterior density of β_2 for models 2 and 4, year/season 1995B.

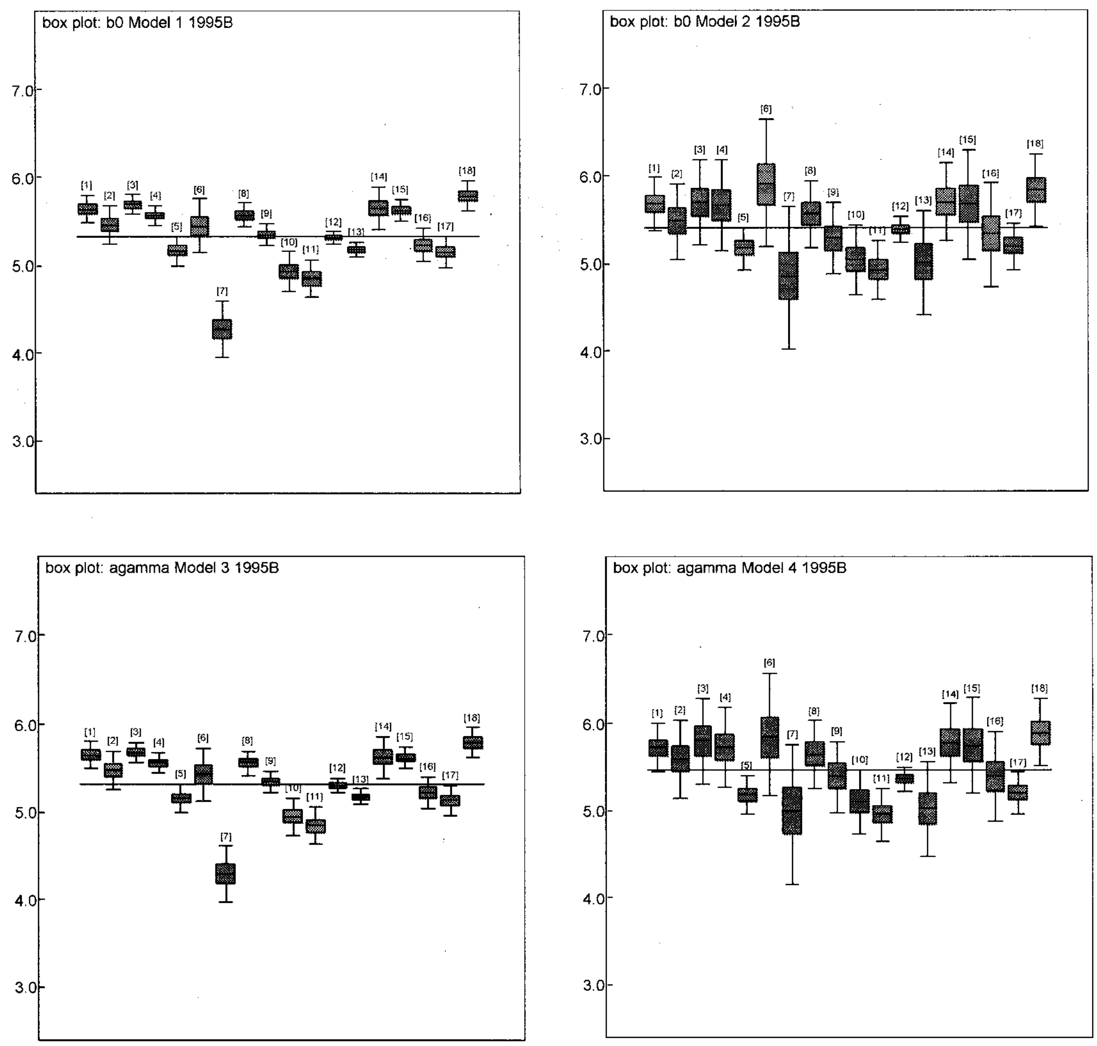


Figure 4.12. Box plots of estimated intercepts (b_{0i}) for models 1 and 2 and Car model intercept equivalents ($a\gamma_i$) for models 3 and 4. Boxes indicate the inter-quartile range while the arms indicate the 2.5% and 97.5% probability limits

Appendix C

4.6.C.1 winBUGS code

Model 1

```
model
{
	for(i in 1:Nareas){
		for(j in 1:Nobs[i]){
			lnCPUE[i, j]~dnorm(mu[i, j], tau.c)
			mu[i, j] <- b0[i] - q[i] * E[i, j]
		}
		# priors
		b0[i] ~ dnorm(mu.b, tau.b)
		q[i] ~ dnorm(mu.q, tau.q)
		}


	# hyperpriors
	tau.c ~ dgamma(0.001, 0.001)
	sigma.c <- 1/sqrt(tau.c)
	tau.b ~ dgamma(0.001, 0.001)
	sigma.b <- 1/sqrt(tau.c)
	tau.q ~ dgamma(0.001, 0.001)
	sigma.q <- 1/sqrt(tau.q)
	mu.b ~ dunif(0, 10)
	mu.q ~ dnorm(0, 1)
}
```

Model 2

```
model
{
	for(i in 1:Nareas){
		for(j in 1:Nobs[i]){
			lnCPUE[i, j]~dnorm(mu[i, j], tau.c)
			mu[i, j] <- b0[i] - q[i] * E[i, j] + beta5 * x5[i] + beta6 * x6[i] + beta7 * x7[i] + beta8 * x8[i]
		}
		# priors
		b0[i] ~ dnorm(mu.b, tau.b)
		q[i] ~ dnorm(mu.q, tau.q)
		}

		beta1 ~ dnorm(0,10)
		beta2 ~ dnorm(0,10)
		beta3 ~ dnorm(0,10)
		beta4 ~ dnorm(0,10)


	# hyperpriors
	tau.c ~ dgamma(0.001, 0.001)
	sigma.c <- 1/sqrt(tau.c)
	tau.b ~ dgamma(0.001, 0.001)
	sigma.b <- 1/sqrt(tau.c)
	tau.q ~ dgamma(0.001, 0.001)
	sigma.q <- 1/sqrt(tau.q)
	mu.b ~ dunif(0, 10)
	mu.q ~ dnorm(0, 1)
}
```

Model 3

```
model
{
	for(i in 1:Nareas){
		for(j in 1:Nobs[i]){
			lnCPUE[i, j]~dnorm(mu[i, j], tau.c)
			mu[i, j] <- b0[i] - q[i] * E[i, j] + alpha0 + gamma[i]
		}
		# priors
		b0[i] <- 0
		q[i] ~ dnorm(mu.q, tau.q)
		agamma[i] <- alpha0 + gamma[i]
		}
		#CAR prior
		gamma[1:Nareas]~car.normal(adj[],weights[],num[],tau.car)
		for(k in 1:sumNumNeigh){
		weights[k] <- 1
		}

		alpha0 ~ dflat()

	# hyperpriors
	tau.car ~ dgamma(0.5, 0.0005)
	sigma.car <-sqrt(1/tau.car)
	tau.c ~ dgamma(0.001, 0.001)
	sigma.c <- 1/sqrt(tau.c)
	tau.q ~ dgamma(0.001, 0.001)
	sigma.q <- 1/sqrt(tau.q)
	mu.q ~ dnorm(0, 1)
}
```

Model 4

```
model
{
	for(i in 1:Nareas){
		for(j in 1:Nobs[i]){
			lnCPUE[i, j]~dnorm(mu[i, j], tau.c)
			mu[i, j] <- b0[i] - q[i] * E[i, j] + alpha0 + beta5 * x5[i] + beta6 * x6[i] + beta7 * x7[i] + beta8 *
x8[i] + gamma[i]
		}
		# priors
		b0[i] <- 0
		q[i] ~ dnorm(mu.q, tau.q)
		agamma[i] <- alpha0 + gamma[i]
		}
		#CAR prior
		gamma[1:Nareas]~car.normal(adj[],weights[],num[],tau.car)
		for(k in 1:sumNumNeigh){
		weights[k] <- 1
		}

		beta1 ~ dnorm(0,10)
		beta2 ~ dnorm(0,10)
		beta3 ~ dnorm(0,10)
		beta4 ~ dnorm(0,10)
		alpha0 ~ dflat()

	# hyperpriors
	tau.car ~ dgamma(0.5, 0.0005)
	sigma.car <-sqrt(1/tau.car)
	tau.c ~ dgamma(0.001, 0.001)
	sigma.c <- 1/sqrt(tau.c)
	tau.q ~ dgamma(0.001, 0.001)
	sigma.q <- 1/sqrt(tau.q)
	mu.q ~ dnorm(0, 1)
```

```
}
```

4.6.C.2 Starting values for the 3 MCMC chains for model 4

```
list(tau.c=1,
tau.q=0.00001,
mu.q=0.0001,
tau.car=1,
q=c(.00001, .00001, .00001, .00001, .00001, .00001, .00001, .00001, .00001, .00001, .00001),
alpha0=0,
beta1=0,
beta2=0,
beta3=0,
beta4=0,
gamma=c(1,1,1,1,1,1,1,1,1,1,1)
)

list(tau.c=2,
tau.q=0.00002,
mu.q=0.0002,
tau.car=1,
alpha0=0,
beta1=0,
beta2=0,
beta3=0,
beta4=0,
q=c(.00002, .00002, .00002, .00002, .00002, .00002, .00002, .00002, .00002, .00002, .00002),
gamma=c(1,1,1,1,1,1,1,1,1,1,1)
)

list(tau.c=3,
tau.q=0.0001,
mu.q=0.001,
tau.car=1,
alpha0=0,
beta1=0,
beta2=0,
beta3=0,
beta4=0,
q=c(.0001, .0001, .0001, .0001, .0001, .0001, .0001, .0001, .0001, .0001, .0001),
gamma=c(1,1,1,1,1,1,1,1,1,1,1)
)
```

4.7.C.3 Point estimates for variables of the 4 Bayesian models for strata 1995B

Model 1

node	mean	sd	MC error	2.50%	median	97.50%
b0[1]	5.632	0.07921	6.04E-04	5.476	5.632	5.787
b0[2]	5.454	0.1107	8.57E-04	5.239	5.453	5.671
b0[3]	5.686	0.0575	3.98E-04	5.573	5.686	5.8
b0[4]	5.56	0.05814	4.01E-04	5.446	5.56	5.674
b0[5]	5.161	0.0823	5.70E-04	5	5.161	5.322
b0[6]	5.439	0.157	0.001099	5.132	5.439	5.749
b0[7]	4.268	0.1624	0.001144	3.949	4.268	4.584
b0[8]	5.564	0.06986	5.32E-04	5.427	5.564	5.701
b0[9]	5.34	0.06206	4.36E-04	5.218	5.34	5.462
b0[10]	4.925	0.1136	8.28E-04	4.702	4.925	5.148

b0[11]	4.846	0.1104	9.13E-04	4.628	4.846	5.06
b0[12]	5.303	0.03648	2.46E-04	5.231	5.303	5.374
b0[13]	5.174	0.04245	2.92E-04	5.091	5.174	5.257
b0[14]	5.639	0.1259	8.44E-04	5.394	5.639	5.887
b0[15]	5.615	0.06172	4.68E-04	5.494	5.615	5.736
b0[16]	5.221	0.09614	6.01E-04	5.034	5.221	5.41
b0[17]	5.146	0.08654	6.06E-04	4.977	5.146	5.316
b0[18]	5.78	0.08595	7.00E-04	5.611	5.78	5.948
mu.b	5.32	0.0993	3.44E-04	5.122	5.32	5.516
mu.q	-3.04E-06	0.00272	8.11E-06	-0.00538	-6.07E-07	0.005366
q[18]	7.37E-06	1.99E-06	1.61E-08	3.47E-06	7.38E-06	1.13E-05
q[17]	3.58E-06	1.09E-06	7.60E-09	1.45E-06	3.58E-06	5.72E-06
q[16]	2.66E-06	1.24E-06	7.71E-09	2.57E-07	2.66E-06	5.09E-06
q[15]	1.33E-06	6.45E-07	4.88E-09	5.74E-08	1.33E-06	2.59E-06
q[14]	-2.47E-05	9.41E-06	6.31E-08	-4.30E-05	-2.48E-05	-6.26E-06
q[13]	7.20E-07	1.02E-07	6.97E-10	5.20E-07	7.20E-07	9.19E-07
q[12]	8.11E-07	7.80E-08	5.28E-10	6.58E-07	8.11E-07	9.64E-07
q[11]	2.87E-06	1.72E-06	1.42E-08	-4.92E-07	2.87E-06	6.20E-06
q[10]	3.59E-06	3.26E-06	2.35E-08	-2.80E-06	3.59E-06	1.00E-05
q[9]	7.34E-07	6.73E-07	4.71E-09	-5.84E-07	7.36E-07	2.05E-06
q[8]	3.96E-06	1.07E-06	8.17E-09	1.85E-06	3.96E-06	6.07E-06
q[7]	1.85E-06	3.35E-06	2.30E-08	-4.72E-06	1.86E-06	8.37E-06
q[6]	7.18E-06	8.08E-06	5.72E-08	-8.65E-06	7.17E-06	2.30E-05
q[5]	2.56E-06	7.70E-07	5.31E-09	1.05E-06	2.56E-06	4.07E-06
q[4]	-2.74E-06	7.92E-07	5.44E-09	-4.28E-06	-2.74E-06	-1.18E-06
q[3]	1.78E-06	5.63E-07	3.94E-09	6.75E-07	1.78E-06	2.88E-06
q[2]	3.89E-07	2.81E-06	2.18E-08	-5.08E-06	3.77E-07	5.91E-06
q[1]	-1.43E-07	1.44E-06	1.09E-08	-2.98E-06	-1.42E-07	2.67E-06
sigma.b	0.7073	0.006144	1.89E-05	0.6954	0.7072	0.7195
sigma.c	0.7073	0.006144	1.89E-05	0.6954	0.7072	0.7195
sigma.q	0.01136	0.002084	6.39E-06	0.008144	0.01106	0.01623
tau.b	6.972	2.724	0.01327	2.863	6.57	13.38
tau.c	1.999	0.03473	1.07E-04	1.932	1.999	2.068
tau.q	8497	2911	8.786	3795	8168	15080

Model 2

b0[1]	5.685	0.3021	0.009702	5.101	5.685	6.282
b0[2]	6.383	0.2581	0.005489	5.897	6.376	6.91
b0[3]	5.649	0.2877	0.008907	5.077	5.648	6.224
b0[4]	6.22	0.4018	0.01099	5.451	6.211	7.039
b0[5]	5.552	0.2237	0.005531	5.116	5.55	5.994
b0[6]	5.618	0.1744	0.004814	5.267	5.62	5.957
b0[7]	5.095	0.5131	0.0171	4.014	5.122	6.039
b0[8]	5.018	0.2779	0.006214	4.463	5.021	5.556
b0[9]	5.645	0.2196	0.004957	5.228	5.641	6.089
b0[10]	5.682	0.254	0.008645	5.152	5.688	6.169

b0[11]	5.74	0.1082	0.002432	5.523	5.742	5.948
b0[12]	5.119	0.1054	0.002535	4.906	5.121	5.32
b0[13]	5.616	0.05652	0.001328	5.504	5.616	5.726
b0[14]	5.595	0.3703	0.0121	4.861	5.592	6.318
b0[15]	5.141	0.1234	0.003335	4.895	5.141	5.38
b0[16]	5.67	0.1279	0.00313	5.417	5.67	5.922
beta5	0.078	0.2406	0.00586	-0.3978	0.07628	0.5503
beta6	0.2888	0.2091	0.004994	-0.1341	0.2939	0.6851
beta7	2.87E-09	1.76E-08	5.92E-10	-3.27E-08	3.02E-09	3.82E-08
beta8	-1.28E-06	2.93E-06	9.98E-08	-7.10E-06	-1.33E-06	4.83E-06
mu.b	5.59	0.1827	0.004617	5.229	5.589	5.957
mu.q	1.76E-06	0.003098	8.00E-06	-0.00613	-9.25E-07	0.006115
q[16]	3.14E-06	2.41E-06	1.61E-08	-1.60E-06	3.14E-06	7.87E-06
q[15]	-8.33E-08	1.08E-06	7.41E-09	-2.20E-06	-8.00E-08	2.02E-06
q[14]	4.90E-06	8.97E-07	5.95E-09	3.14E-06	4.90E-06	6.67E-06
q[13]	1.34E-06	1.71E-07	1.20E-09	1.01E-06	1.35E-06	1.68E-06
q[12]	-2.93E-06	1.18E-06	7.90E-09	-5.23E-06	-2.93E-06	-6.32E-07
q[11]	2.84E-06	1.51E-06	1.06E-08	-1.07E-07	2.83E-06	5.81E-06
q[10]	9.36E-07	8.94E-08	6.12E-10	7.61E-07	9.36E-07	1.11E-06
q[9]	8.64E-06	2.64E-06	1.79E-08	3.47E-06	8.64E-06	1.38E-05
q[8]	9.11E-06	1.32E-05	1.13E-07	-1.70E-05	9.16E-06	3.47E-05
q[7]	1.73E-06	8.21E-07	6.18E-09	1.20E-07	1.73E-06	3.32E-06
q[6]	-1.53E-07	2.18E-06	1.58E-08	-4.45E-06	-1.45E-07	4.11E-06
q[5]	2.51E-07	3.24E-06	2.16E-08	-6.07E-06	2.40E-07	6.61E-06
q[4]	-9.89E-06	4.86E-05	5.40E-07	-1.04E-04	-1.03E-05	8.64E-05
q[3]	-6.82E-07	1.10E-06	6.97E-09	-2.83E-06	-6.86E-07	1.47E-06
q[2]	1.62E-06	1.88E-05	1.35E-07	-3.50E-05	1.59E-06	3.86E-05
q[1]	-1.19E-06	7.08E-07	4.61E-09	-2.57E-06	-1.19E-06	2.01E-07
sigma.b	0.7114	0.006279	1.71E-05	0.6993	0.7114	0.7239
sigma.c	0.7114	0.006279	1.71E-05	0.6993	0.7114	0.7239
sigma.q	0.01216	0.002408	6.78E-06	0.008539	0.0118	0.01788
tau.b	5.719	2.873	0.04059	1.838	5.172	12.81
tau.c	1.976	0.03488	9.49E-05	1.908	1.976	2.045
tau.q	7510	2739	7.467	3129	7181	13710

Model 3

agamma[1]	5.645	0.07948	0.001003	5.49	5.645	5.8
agamma[2]	5.478	0.1108	0.001351	5.258	5.479	5.694
agamma[3]	5.679	0.05887	6.49E-04	5.563	5.679	5.794
agamma[4]	5.559	0.06011	6.33E-04	5.442	5.559	5.677
agamma[5]	5.156	0.08177	8.86E-04	4.995	5.156	5.317
agamma[6]	5.424	0.1543	0.001728	5.124	5.423	5.728
agamma[7]	4.297	0.1632	0.001767	3.977	4.298	4.614
agamma[8]	5.561	0.06983	8.18E-04	5.422	5.561	5.697
agamma[9]	5.347	0.06323	7.00E-04	5.223	5.348	5.471
agamma[10]	4.948	0.1082	0.001149	4.734	4.948	5.158

agamma[11]	4.844	0.1075	0.001334	4.633	4.844	5.054
agamma[12]	5.3	0.04098	4.12E-04	5.22	5.3	5.381
agamma[13]	5.174	0.04585	4.80E-04	5.085	5.174	5.264
agamma[14]	5.622	0.1213	0.001279	5.385	5.621	5.86
agamma[15]	5.612	0.06297	7.07E-04	5.49	5.612	5.735
agamma[16]	5.222	0.09176	8.97E-04	5.042	5.222	5.402
agamma[17]	5.134	0.08517	9.66E-04	4.966	5.135	5.301
agamma[18]	5.79	0.08626	0.001056	5.621	5.789	5.959
alpha0	5.322	0.01992	2.53E-04	5.283	5.322	5.36
gamma[1]	0.3234	0.07795	9.70E-04	0.1719	0.3235	0.4749
gamma[2]	0.1565	0.108	0.001305	-0.05729	0.1575	0.3667
gamma[3]	0.3572	0.05796	6.82E-04	0.2439	0.3573	0.4708
gamma[4]	0.2371	0.05908	6.39E-04	0.1219	0.2372	0.3529
gamma[5]	-0.1661	0.07999	8.66E-04	-0.3229	-0.1661	-0.009407
gamma[6]	0.1027	0.1506	0.001639	-0.19	0.1016	0.4008
gamma[7]	-1.025	0.1594	0.001704	-1.337	-1.024	-0.7144
gamma[8]	0.2389	0.06855	8.28E-04	0.1033	0.2394	0.3725
gamma[9]	0.02574	0.06164	6.83E-04	-0.09498	0.02623	0.146
gamma[10]	-0.3737	0.1054	0.001099	-0.5824	-0.3734	-0.1688
gamma[11]	-0.478	0.1041	0.001274	-0.6841	-0.4777	-0.2731
gamma[12]	-0.0214	0.04093	4.64E-04	-0.1016	-0.02149	0.05899
gamma[13]	-0.1478	0.04538	4.99E-04	-0.2366	-0.148	-0.05923
gamma[14]	0.2998	0.1189	0.001244	0.06722	0.2993	0.534
gamma[15]	0.2902	0.06176	7.24E-04	0.1701	0.2902	0.4111
gamma[16]	-0.1	0.09004	8.56E-04	-0.2767	-0.1004	0.07653
gamma[17]	-0.1876	0.08337	9.40E-04	-0.3514	-0.1874	-0.02533
gamma[18]	0.4679	0.08403	0.001024	0.3034	0.4676	0.6336
mu.q	-1.39E-05	0.002704	1.29E-05	-0.005381	-1.02E-05	0.005347
q[1]	6.48E-08	1.45E-06	1.84E-08	-2.76E-06	6.36E-08	2.88E-06
q[2]	9.24E-07	2.81E-06	3.43E-08	-4.64E-06	9.35E-07	6.40E-06
q[3]	1.72E-06	5.71E-07	6.36E-09	5.98E-07	1.72E-06	2.83E-06
q[4]	-2.75E-06	8.12E-07	8.80E-09	-4.34E-06	-2.75E-06	-1.16E-06
q[5]	2.52E-06	7.68E-07	8.31E-09	1.01E-06	2.51E-06	4.03E-06
q[6]	6.57E-06	7.97E-06	8.87E-08	-9.08E-06	6.57E-06	2.22E-05
q[7]	2.34E-06	3.37E-06	3.59E-08	-4.29E-06	2.33E-06	8.94E-06
q[8]	3.92E-06	1.08E-06	1.28E-08	1.79E-06	3.92E-06	6.02E-06
q[9]	8.03E-07	6.83E-07	7.57E-09	-5.49E-07	8.07E-07	2.13E-06
q[10]	4.16E-06	3.14E-06	3.25E-08	-2.08E-06	4.18E-06	1.03E-05
q[11]	2.83E-06	1.69E-06	2.10E-08	-4.78E-07	2.84E-06	6.12E-06
q[12]	8.07E-07	8.49E-08	8.90E-10	6.41E-07	8.07E-07	9.74E-07
q[13]	7.19E-07	1.07E-07	1.15E-09	5.08E-07	7.19E-07	9.29E-07
q[14]	-2.59E-05	9.19E-06	9.57E-08	-4.39E-05	-2.59E-05	-7.87E-06
q[15]	1.30E-06	6.54E-07	7.33E-09	3.64E-08	1.30E-06	2.59E-06
q[16]	2.67E-06	1.19E-06	1.18E-08	3.38E-07	2.67E-06	5.01E-06
q[17]	3.45E-06	1.07E-06	1.20E-08	1.35E-06	3.46E-06	5.56E-06
q[18]	7.56E-06	2.00E-06	2.48E-08	3.65E-06	7.56E-06	1.15E-05
sigma.c	0.7074	0.00615	2.71E-05	0.6954	0.7074	0.7195
sigma.car	0.7264	0.147	0.001052	0.4952	0.7082	1.067

sigma.q	0.01137	0.002086	1.01E-05	0.00816	0.01107	0.01621
tau.c	1.999	0.03476	1.54E-04	1.931	1.998	2.068
tau.car	2.123	0.8318	0.006202	0.8781	1.994	4.078
tau.q	8480	2897	14.05	3803	8156	15020

Model 4

agamma[1]	5.718	0.1404	0.004458	5.447	5.717	5.997
agamma[2]	5.594	0.2239	0.006974	5.14	5.596	6.027
agamma[3]	5.8	0.2493	0.008868	5.297	5.8	6.281
agamma[4]	5.722	0.2314	0.008413	5.263	5.718	6.174
agamma[5]	5.183	0.1122	0.002987	4.963	5.184	5.402
agamma[6]	5.845	0.3547	0.008654	5.171	5.835	6.571
agamma[7]	4.993	0.41	0.0117	4.149	5.004	5.762
agamma[8]	5.649	0.1993	0.006508	5.246	5.651	6.025
agamma[9]	5.395	0.2079	0.00711	4.978	5.397	5.79
agamma[10]	5.104	0.1863	0.00565	4.729	5.106	5.463
agamma[11]	4.958	0.1533	0.004213	4.656	4.961	5.254
agamma[12]	5.368	0.07077	0.002027	5.226	5.369	5.504
agamma[13]	5.025	0.2768	0.01006	4.476	5.026	5.567
agamma[14]	5.78	0.2315	0.006974	5.317	5.781	6.221
agamma[15]	5.747	0.2764	0.01029	5.204	5.744	6.287
agamma[16]	5.393	0.259	0.009136	4.877	5.391	5.907
agamma[17]	5.202	0.1199	0.003248	4.966	5.201	5.439
agamma[18]	5.888	0.193	0.006555	5.515	5.883	6.273
alpha0	5.465	0.1559	0.005598	5.147	5.467	5.765
gamma[1]	0.2537	0.1051	0.002293	0.04759	0.2534	0.4618
gamma[2]	0.1298	0.1413	0.003004	-0.1482	0.1308	0.4038
gamma[3]	0.3352	0.1267	0.003859	0.08821	0.3351	0.5822
gamma[4]	0.2569	0.121	0.00377	0.02225	0.2562	0.4971
gamma[5]	-0.2813	0.1227	0.00316	-0.5187	-0.2823	-0.03504
gamma[6]	0.3801	0.3223	0.008517	-0.2376	0.3722	1.037
gamma[7]	-0.472	0.3075	0.007771	-1.1	-0.4636	0.1087
gamma[8]	0.1848	0.1224	0.003143	-0.05785	0.1843	0.4252
gamma[9]	-0.06987	0.1233	0.003232	-0.3147	-0.06892	0.1683
gamma[10]	-0.3609	0.1206	0.002186	-0.6015	-0.3592	-0.1287
gamma[11]	-0.5062	0.1242	0.002548	-0.7504	-0.5061	-0.2608
gamma[12]	-0.09688	0.191	0.007163	-0.4685	-0.0945	0.2884
gamma[13]	-0.4394	0.2356	0.008412	-0.8939	-0.4397	0.02871
gamma[14]	0.3149	0.1474	0.002975	0.02738	0.3142	0.6057
gamma[15]	0.2827	0.1624	0.005502	-0.02736	0.2814	0.6072
gamma[16]	-0.0716	0.1518	0.004445	-0.369	-0.07222	0.2275
gamma[17]	-0.2627	0.1193	0.002964	-0.4897	-0.2641	-0.02481
gamma[18]	0.4229	0.1146	0.002522	0.2025	0.4217	0.6505

beta5	0.1737	0.2495	0.008656	-0.3133	0.1735	0.6585
beta6	0.01322	0.2075	0.007335	-0.3833	0.01295	0.433
beta7	-7.82E-10	1.43E-08	5.41E-10	-2.91E-08	-4.38E-10	2.68E-08
beta8	-8.32E-07	1.72E-06	6.36E-08	-4.11E-06	-8.60E-07	2.63E-06
mu.q	-3.82E-06	0.002729	9.83E-06	-0.00539	4.29E-06	0.005425
q[1]	6.54E-08	1.47E-06	1.41E-08	-2.81E-06	6.21E-08	2.95E-06
q[2]	1.02E-06	2.80E-06	2.78E-08	-4.50E-06	1.03E-06	6.46E-06
q[3]	1.73E-06	5.79E-07	5.08E-09	5.88E-07	1.73E-06	2.85E-06
q[4]	-2.78E-06	8.10E-07	7.05E-09	-4.38E-06	-2.78E-06	-1.19E-06
q[5]	2.55E-06	7.64E-07	6.55E-09	1.05E-06	2.56E-06	4.04E-06
q[6]	2.33E-06	8.39E-06	8.07E-08	-1.41E-05	2.35E-06	1.87E-05
q[7]	1.05E-06	3.32E-06	3.15E-08	-5.40E-06	1.05E-06	7.60E-06
q[8]	4.01E-06	1.09E-06	9.77E-09	1.89E-06	4.00E-06	6.15E-06
q[9]	8.79E-07	6.89E-07	6.22E-09	-4.73E-07	8.81E-07	2.23E-06
q[10]	4.22E-06	3.16E-06	3.09E-08	-1.99E-06	4.23E-06	1.04E-05
q[11]	2.91E-06	1.66E-06	1.68E-08	-3.61E-07	2.91E-06	6.17E-06
q[12]	8.07E-07	8.65E-08	6.53E-10	6.37E-07	8.06E-07	9.76E-07
q[13]	7.28E-07	1.08E-07	8.84E-10	5.17E-07	7.28E-07	9.41E-07
q[14]	-2.58E-05	9.18E-06	7.57E-08	-4.40E-05	-2.58E-05	-7.97E-06
q[15]	1.28E-06	6.59E-07	6.14E-09	-5.51E-09	1.28E-06	2.58E-06
q[16]	2.58E-06	1.21E-06	1.04E-08	2.28E-07	2.57E-06	4.95E-06
q[17]	3.51E-06	1.07E-06	9.59E-09	1.42E-06	3.51E-06	5.61E-06
q[18]	7.56E-06	2.01E-06	1.93E-08	3.62E-06	7.57E-06	1.15E-05
sigma.c	0.7074	0.006133	2.41E-05	0.6955	0.7074	0.7195
sigma.car	0.6801	0.1486	0.001844	0.4476	0.6604	1.029
sigma.q	0.01136	0.002101	8.01E-06	0.008139	0.01106	0.01633
tau.c	1.999	0.03466	1.36E-04	1.932	1.999	2.068
tau.car	2.467	1.048	0.0119	0.9447	2.293	4.992
tau.q	8504	2922	11.14	3752	8176	15090

General Summary and Conclusions

Catch information for the pollock fishery is collected from three sources: the North Pacific Fishery Management Council (NPFMC) observer program, Alaska Department of Fish and Game (ADF&G) fish tickets and National Marine Fisheries Service (NMFS) weekly processor reports. Prior to the year 2000, these data were amalgamated by management entities in two ways to account for the entire pollock fishery and to enforce and set regulations. The catch-by-vessel (CBV) database was specifically designed and used to allocate catch quotas to vessels while the Blend database was designed to monitor general fishery activities. Both used different percentages of the three data collection methods to account for the pollock catch. Our requirements for successful implementation of the DeLury depletion estimator required fishing effort and catch to be recorded on the finest temporal and spatial scales possible. The observer program is the best source for this information; however, both the CBV and Blend databases have forsaken significant percentages of the observer program in favor of the other two sources. We designed a data processing algorithm that would account for 100% of the pollock catch that used all available observer program data with gaps filled in by first the fish tickets and second the weekly processor reports (chapter 1). This resulted in a database with 90% observer program data giving haul location to the nearest minute in latitude and longitude, haul time, our measure of effort, to the nearest minute and catch in weight to the nearest hundredth of a kilogram. Another 10% of the data came from fish tickets, which gives location to the nearest ADF&G reporting area, an approximately 30 by 34.5 nm block, with the best measure of effort being the number of days in a fishing trip. An insignificant amount of data came from the weekly processor reports that give catch estimates pooled over a week and location to the irregular and large federal reporting areas. While the scale of data associated with the catch became finer, the overall catch weight agreed to within 5% or better of the CBV and Blend for the five years, 1995-1999, that were examined.

As fisheries management entertains more complex objectives to ensure sustainable fisheries and ecosystems, a focus on fine spatial and temporal scales is becoming more common. Efficient use of available data resources will be increasingly demanded for such assessments on limited budgets. Subsequent to the creation of our database, the NMFS created a database, called the Catch Accounting System, which also makes better use of the fine spatial and temporal data, relative to the CBV and Blend. We applaud this effort and encourage further steps to maximizing the use of data that are already being collected.

The second stage of this work (chapter 2) standardized the catch and effort data to eliminate variability that may hide the depletion signal. Data were stratified by year, season, and ADF&G reporting area prior to standardization. The stratification was implemented for a number of reasons. It was necessary to meet the assumptions of GLMs, as many factor combinations would have not had any data because our vessel id factor had many different levels and varied greatly across strata. The downside was that many separate models were required, which greatly increased computational time (approximately 8,350 models to run and analyze). Another reason was that the stratification eliminates the need to standardize the variability associated with the different strata. The stratification procedure also followed the stratification that the DeLury depletion estimator would use. However, the stratification procedure made it difficult to compare results among strata.

A general linear model (GLM) was used to standardize the data. Typically, vessel characteristics are used as covariates in standardization. However, because our goal was to eliminate the most variability in the data not associated with the depletion signal, we used individual vessel identification numbers; which showed that an individual vessel had a characteristic CPUE signature that differed greatly from other vessels. The percentage of pollock in the haul and its quadratic were found to be significant factors in explaining CPUE while the speed of the haul and its quadratic and if the haul was taken during the day or night were less effective. Over all, approximately 50% of the variability was removed from the data due to the stratification procedure and GLMs. We made use of response surface analysis to better understand the biological results of the GLMs relative to the factors. Because so much of the variability was eliminated by the individual vessel identification numbers, the other factors had less biological meaning associated with them and were primarily fitting variables. Post hoc analysis of the vessel ID coefficients did provide some insight into vessel related characterization of the fishery. This indicated that larger vessels tended to have higher CPUEs, but this relationship differed between dedicated catcher vessels and offshore catcher processors.

The third stage of this work (chapter 3) is the analysis of the DeLury depletion estimator. Areas chosen for analysis were those that had the largest amount of catch by weight and those areas in and around the Critical Habitat Catcher Vessel Operational

Area (CHCVOA) in the eastern Bering Sea. These areas were chosen based on their importance to the Steller sea lion and our expectation that depletion would be most likely in the areas of greatest fishing effort. We used the standard DeLury model with natural mortality:

$$\ln U_t = \ln(qB_0) - qE_t - Mt$$

in which U_t is the CPUE, B_0 is the initial biomass and E_t is cumulative effort over time. This results in a standard regression equation with the slope being the catchability (q); in which a significantly negative slope indicates depletion is occurring.

We used data from the two seasons in the years 1995-1998 and the four seasons in 1999. Of 237 depletion estimates, 172 had negative slopes, 94 of which were statistically significant, a greater number than would be expected by chance alone when pooled by individual years and all years together. Of the 65 positive slopes, 19 were significantly positive which is also more than would be expected by chance but only when all years are pooled together. The statistically significant depleted areas tended to occur in areas just north of Dutch Harbor, though depletion was found throughout the eastern Bering Sea where the pollock fishing fleet operates. We estimated the global catchability of the pollock fishery seasonally from information in the NMFS Stock Assessment and Fishery Evaluation (SAFE) document and found it to generally be much larger than the catchabilities we estimated. 65% of our catchabilities were smaller (in absolute terms) than the SAFE, 50% were at least half the size or smaller, and 25% were at least an order of magnitude smaller. General linear models associating the estimated cumulative depletion or catchability with spatial, environmental, and fishery characteristics indicated that as total catch and effort increased, depletion decreased, and as initial biomass increased, depletion decreased. These correlations and the general differences between the SAFE and DeLury catchability estimates can be explained by a hyperstable relationship between CPUE and abundance in which the CPUE has a nonlinear relationship with abundance with the CPUE staying higher than would be expected. This relationship is a result of the schooling behavior of pollock, the fish finding capability of modern fishing vessels, and the omission of search time in our measure of effort. In general this would mean that it would be more difficult to determine a statistically significant finding for depletion because the slope of the hyperstable curve is smaller in areas of higher biomass than a standard linear relationship between abundance and CPUE. As such, our findings of depletion likely err on the side of finding of less depletion.

While it is clear that statistically significant depletion occurred as a result of the pollock fishery, our analysis did reveal that it may take only a couple of weeks for a depleted population to recover from recruitment or migration as one rare time series that had a break between times of fishing effort clearly showed. Evidence also indicates that when the fishery was dispersed in space, the concentration of depletion near Dutch Harbor decreased. This occurred naturally in the B season relative to the A season when fishing migrates north towards St Mathew Island. It also occurred in 1999 when measures to protect the Steller sea lion and the American Fisheries Act were implemented. Season 1999A was the only season we investigated that did not show any evidence of depletion. Unfortunately, we were unable to directly relate our depletion estimates to the harvest rate of the SAFE so quantifying the depletion in more specific terms was not possible.

The final stage of this work (chapter 4) entailed a hierarchical spatial Bayesian treatment of the DeLury depletion estimator using data from the 29 ADF&G areas in and around the CHCVOA. We used spatial and fishery related covariates as in the third chapter and we also investigated the use of a conditional autoregressive (CAR) model to explain any possible spatial autocorrelation that may exist in the estimate of catchability. We examined four models, the basic hierarchical Bayesian model in which the hierarchy consists of areas within a season, the basic model with spatial/fishery characteristics covariates, the basic model with the CAR model, and a model with both the CAR and covariates. The advantages of a Bayesian analysis typically include a reduction in the variability of parameter estimates and an ability to characterize the fishery in more general terms by means of umbrella distributions, the distributions of the hyper priors that form the hierarchy. In this case we assumed that the catchabilities are similar enough over the areas that they can be drawn from an umbrella normal distribution.

Our results for the Bayesian analysis were not appreciably different from the traditional frequentist analysis of chapter 3. Of the 153 ADF&G areas in each of the 5 years, the net number of areas with significant depletion changed by only 2-5 for each of the 4 models. The difference between the Bayesian and frequentist parameter estimates were largest for those areas with the fewest parameters indicating that the Bayesian method tended to reign in those areas to some degree, however the variability estimates for the Bayesian analysis tended to be slightly larger. The spatial/fishery characteristics covariates were rarely significantly different from zero. The CAR parameterization did not alter the results in a significant way. There are a number of reasons why the CAR model may have been inappropriate. (1) Our spatial scale for pooling data may have been inappropriate, (2) the lattice boarders did not conform to the natural spatial structure, (3) no spatial structure existed. The results of the Bayesian analysis primarily indicate that we have extracted as much information about depletion in the eastern Bering Sea that is available in this data set while confirming that the eastern Bering Sea has been subjected to significant fishery induced depletion. This is also a first step into combining Bayesian methodology with autoregressive spatial models in the fisheries community.

The research for the first three chapters is technically and conceptually straightforward. The standardization was carried out like in other studies except for stratification prior to standardization. The stratification process is time intensive and only worth undertaking if the process can be automated or the final product requires such organization. I would also recommend using only the vessel ID as a factor for standardization and include other variables only if there is very good reason to believe they have a strong effect of catchability. Time on more complex models with variables of dubious worth is probably not well spent. The DeLury method itself is a well-known and traditional methodology for population estimation. It is relatively simple compared to many of today's computationally and data-intensive methods, particularly those used in fisheries stock assessments. One of our major data issues was with targeting information. Targeting information could be easily included in observer reports indicating primary and secondary targets; this would eliminate guesswork and arbitrary lines to determine which data to include. The new Catch Accounting System records targeting information. Because CPUE data is still used to tune many stock assessments, having accurate targeting information would clearly have practical and immediate applications. The final chapter is the most advanced theoretical chapter. Bayesian methods have found their way into fisheries stock assessment and the primary literature in the last decade. Our hierarchical application is commonly seen in the fisheries literature. The addition of the spatial CAR and related models to Bayes has been accelerating in the last few years in other fields, probably due to the WinBUGS program making Bayesian applications relatively simple. Becoming familiar with this program is the best first step for those interested in spatial Bayesian techniques, because it has extensive information and examples on the subject in a relatively easy-to-learn format. The combination of Bayes and spatial models has not yet found its way into fisheries literature. Considering the spatial nature of fisheries, there is a relative paucity of fisheries spatial-oriented literature in general. This field in general has considerable room for growth in application and theory in fisheries.

Returning to the original motivation for this research, the decline of the Steller sea lion and the pollock fishery, it is clear that we have detected statistically significant depletion in the eastern Bering Sea. Statistical significance does not necessarily indicate biological significance, as statistically significant findings can be found for relatively small biological differences. Hence, further research is necessary and links in the chain must be connected before the pollock fishery can be implicated in the decline of the Steller sea lion. While some evidence exists that food limitation has occurred in Steller sea lions, it has not been established that the food limitation is due to a lack of pollock in the diet. In addition, while the pollock fishery is competing to some degree with sea lions for pollock, it is not known at what level this competition begins to negatively impact the ability of sea lions to obtain food. Considering the pollock biomass that resides in the eastern Bering Sea, it seems unlikely that a lack of pollock could be contributing to the decline of the sea lion. However, the temporal and spatial pattern of the depletion could be disproportionately important to certain life stages of the sea lion. Further research should focus on solving these problems. Specifically, the relationship between CPUE and abundance should be determined. With this, one could better link the measures of depletion with harvest rates to quantify in absolute terms the depletion that is occurring. Coupling this with more attention to the spatial details and the life history of pollock, particularly their seasonal migration patterns, we would have a better idea of when and where depletion is occurring and how much is due to the pollock fishing industry.